PARALLEL INTERFERENCE CANCELLATION SCHEMES BASED ON ADAPTIVE MMSE DETECTION FOR DS-CDMA SYSTEMS

DU LIN

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DU LIN
(B.Eng., Xi'an Jiaotong University)

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SUMMARY

Direct-sequence code-division multiple access (DS-CDMA) is a popular wireless technology. The conventional detector for this system, known as the matched filter (MF) detector, may cause the problem of multiple access interference (MAI) which limits the capacity and performance of the DS-CDMA systems. To overcome this problem, there has been great interest in the study of multiuser detection techniques.

Among the multiuser detectors, parallel interference cancellation (PIC) detector and adaptive minimum mean square error (MMSE) detectors are attractive for their low complexity and good performance. In this thesis, the fundamental multiuser detectors are studied and based on PIC and MMSE detectors two novel multiuser schemes are proposed:

- Adaptive PIC (APIC) detector, where simple blind adaptive MMSE (BAMMSE) detectors are used for data estimation in each stage instead of MFs which are used in the conventional PIC (CPIC) detector.

- Adaptive decision feedback PIC (ADFPIC) detector, which is an improvement to APIC, where a decision feedback scheme is suggested, *i.e.*, the data estimates in the final stage are used to update the BAMMSE detectors in the previous stages.

For the PIC detectors, as the estimates from the previous stages improve, the performance of the multistage PIC is improved as a result. In the CPIC detector, the data estimates in each stage are derived from the MFs, which suffer from near-far problem, and thus limit the performance of PIC. BAMMSE detector is the decision-directed version of adaptive MMSE, which is shown to have improved performance than MF and keep simplicity in the mean time. As a result, in the APIC scheme, we combine the interference cancellation property of PIC and the accuracy of data estimates of BAMMSE detector. Through both analytical and simulation studies in synchronous Additive White Gaussian Noise (AWGN) channel, the proposed APIC scheme is shown to outperform the CPIC and BAMMSE detectors.

In distorted channel (e.g. asynchronous channel or fading channel), as the error rates increase, the performance of BAMMSE detector degrades. To mitigate this problem, we employ a decision feedback scheme based on the APIC to derive an ADFPIC detector. In this scheme, the data estimates in the final stage are used to update the BAMMSE detectors in the previous stages. Using this decision feedback scheme, we can get more accurate tentative data estimates, which result in effective MAI cancellation. The simulation studies in the asynchronous channel as well as multipath fading channel have shown that the ADFPIC detector always outperforms the APIC.

NOMENCLATURE

ADFPIC	Adaptive Decision Feedback Parallel Interference Cancellation
APIC	Adaptive Parallel Interference Cancellation
AWGN	Additive White Gaussian Noise
BAMMSE	Blind Adaptive Minimum Mean Square Error
BER	Bit Error Rate
BPSK	Binary Phase Shift Keying
BS	Base Station
CDMA	Code Division Multiple Accessing
CPIC	Conventional Parallel Interference Cancellation
DS	Direct Sequence
FDMA	Frequency Division Multiple Access
FH	Frequency Hopping
FIR	Finite Impulse Response
HD	Hard Decision
LMS	Least Mean Squares
LFSR	Linear Feedback Shift Register
MAI	Multiple Access Interference
MF	Matched Filter
MSE	Mean Square Error
MMSE	Minimum Mean Square Error
ML	Maximum Likelihood

MLS	Maximum Likelihood Sequence
NFR	Near Far Ratio
PG	Processing Gain
PN	Pseudorandom Noise
PIC	Parallel Interference Cancellation
RLS	Recursive Least Squares
SD	Soft Decision
SDM	Steepest Descent Method
SIC	Successive Interference Cancellation
SS	Spread Spectrum
SNR	Signal to Noise Ratio
TDL	Tapped Delay Line
TDMA	Time-Division Multiple Access
TH	Time Hopping

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CHAPTER 1

INTRODUCTION

The world is demanding more from wireless communication technologies than ever before. More and more people around the world are subscribing to wireless services. With available frequency resources being saturated, how to share the available communications bandwidth efficiently among increasing number of customers becomes a major concern. After a long debate about the methods for multiple access, code-division multiple access (CDMA) [1, Chapter 13] has emerged as one of the widely accepted multiple access schemes in wireless medium.

1.1 CDMA Systems

Commercially introduced in 1995, CDMA quickly became one of the world's fastest-growing wireless technologies. Different from the traditional ways such as frequency-division multiple access (FDMA) and time-division multiple access (TDMA), where users are orthogonal along frequency or time, CDMA allocates all frequency and time resources to all users simultaneously. To do this, it uses a technique known as Spread Spectrum (SS). In effect, each user is assigned a unique high frequency signature code which spreads its signal bandwidth in such a way that only the same code can recover it at the receiver end.

CDMA possesses many attractive attributes distinguishing it from other multiple access techniques [1,2]. The most important of those relates to the wideband nature of CDMA signals. This is particularly attractive in terrestrial wireless communications which are often subject to severe multipath fading channel conditions. Another significant attribute of CDMA in a multi-cell environment is the possibility of improving the overall system capacity. CDMA signals are also immune to external sources of interference, such as from narrowband communication systems. This provides the potential for multiple communication systems of overlay spectral resources.

There are basically three principal types of spectrum spreading techniques:

- i Direct Sequence (DS) spreading,
- ii Frequency Hopping (FH),
- iii Time Hopping (TH).

In DS-CDMA systems, each user is assigned a unique spreading code upon which the data sequence to be transmitted is modulated. In FH-CDMA systems, each user transmits the data on a narrow-band frequency slot, which changes according to a pre-assigned pattern determined by the spreading code. The TH systems are analogous to FH systems in that TH systems use a pseudo-random code to specify at which times to transmit the narrowband message signal. Among these and other hybrid spread spectrum formats, DS-CDMA is the most popular of CDMA techniques because of its many attractive properties for wireless medium [2,3]. Therefore, we will focus on DS-CDMA systems in this thesis.

1.2 Multiuser Detection Schemes for DS-CDMA Systems

Conventional detector for the DS-CDMA systems follows a single user detection strategy, in which each user is detected separately without regard for other users. Each receiver performs a simple correlation between the received baseband signal and the corresponding user's spreading code. In an additive white Gaussian noise (AWGN) channel with mutually orthogonal spreading codes for all users, this approach would be optimal. However, in practice, it is difficult to have perfectly orthogonal spreading codes, especially in the asynchronous system[*], and thus, the problem of the multiple access interference (MAI) arises. MAI refers to the interference between direct-sequence users. Therefore, despite its simplicity, the conventional detector suffers from MAI. The effect of MAI on system performance is even more pronounced if the users' signals arrive at the receiver at different powers: weaker users may be overwhelmed by stronger users — known as the near-far problem.

A better detection strategy for the DS-CDMA systems is the multiuser detection (also known as joint detection). In this scheme, unlike the conventional detection, information about multiple users is used jointly to detect each individual user. In cellular DS-CDMA systems, each mobile is concerned only with its own signal while the base station (BS) must detect all the signals in its cell. Thus the mobile has the information only about itself, while the BS has information on all the mobiles in its cell. That is, the detector at the BS has knowledge of all the in-cell users' spreading codes and other information. Therefore, by making use of this knowledge, it is easier

[*]In the thesis, synchronous system refers to bit-synchronous system, where bits from all users arrive at the receiver synchronously. Conversely, if there is no timing control, the system is said to be asynchronous system.

to perform multiuser detection in BS. Moreover, taking into account the practical reasons, such as cost, size and weight, multiuser detection has primarily been considered for use at the BS [4,5].

The initial work on multiuser detection is the optimal maximum likelihood sequence (MLS) detector [6, Chapter4]. However, the complexity of this detector grows exponentially with the number of users and the length of the bit sequences, which makes it unsuitable for practical implementation. This necessitated the need for suboptimum multiuser detectors which are robust to near-far problem with a reasonable computational complexity to ensure their practical implementation. Numerous suboptimal approaches have been proposed, the majority of them can be split into two types: linear detectors and subtractive interference cancellation detectors.

In linear multiuser detection schemes, a linear transform is applied to the soft outputs of the conventional detector to produce a new, hopefully better set of outputs. Two of the most important linear detectors are the decorrelating and the minimum mean square error (MMSE) detectors [7,8,9]. Both these detectors need to calculate the inverse of the cross-correlation matrix, the complexity of which is $O(K^3)$ where K is the number of active users [5]. A variety of adaptive strategies have been developed for approximating these detectors, based on algorithms such as the least mean squares (LMS) algorithm, the recursive least squares (RLS) algorithm, the steepest descent method (SDM) and the profound as well as powerful Kalman filtering algorithms [10,11,12]. The MMSE detector lends itself to adaptive implementation more readily than the decorrelating detector because of its natural link to adaptive filtering techniques [12]. The adaptive MMSE detector was first proposed in [9] and analyzed in [13], and is shown to provide significant performance gains relative to the conventional detector.

The other group of detectors is based on the interference cancellation. The principle underlying these detectors is to estimate and then cancel the interference seen by each user. Low complexity is the major advantage of this strategy. This category of detectors includes successive interference cancellation (SIC) and parallel interference cancellation (PIC) [14-16]. Although SIC requires only small amount of additional complexity compared to conventional detector [5], it faces the problem of power reordering and large delays. An alternative approach to SIC is PIC detector. The performance of the PIC is dependent on the estimates of the interfering bits. As the estimates improve, the performance of PIC can also be improved.

1.3 Motivation for the Present Work

The performance and capacity of conventional DS-CDMA system is mainly limited by the MAI. Many advanced signal processing techniques have therefore been proposed to enhance the performance of DS-CDMA systems, and one of them is multiuser detection.

The optimal multiuser detector is extremely difficult for real time implementation. Sub-optimal approaches, including the linear detectors and the interference cancellation detectors, are thus being sought.

In interference cancellation schemes, PIC is one of the most promising schemes. It has low complexity and potential to achieve considerable improvement over the linear detectors, especially in near-far situations. However, its performance is dependent on the reliability of the data estimates. In the conventional PIC (CPIC), tentative data decisions are derived from the conventional detectors, which result in relatively poor performance. Among linear detectors, the adaptive MMSE detector is attractive for its simple structure and superior performance compared to the conventional detector. These properties of PIC and adaptive MMSE schemes provided the motivation to combine these two detectors to come up with better detectors. Accordingly, in this thesis, two novel PIC schemes based on adaptive MMSE detectors are proposed. One is an adaptive PIC (APIC), which uses simple blind adaptive MMSE (BAMMSE) detectors for data estimation to replace conventional detectors (in CPIC). The BAMMSE detector used here only requires the information that is normally provided to the conventional detector and performs better than the conventional one. Another one is an adaptive decision feedback PIC (ADFPIC), which applies a decision feedback scheme in APIC to achieve further performance improvement in distorted channel.

1.4 Outline of the Thesis

The remainder of this thesis is organized as follows.

Chapter 2 contains an introduction to DS-CDMA systems. It includes the description of the system model and the properties of spreading codes. The conventional detector for such systems is also described in this chapter.

Chapter 3 gives an overview of various multiuser detection techniques in the literature. The advantages and disadvantages of these detectors are briefly explained. Based on the discussion of the existing detectors, we propose the idea of combining PIC with adaptive MMSE detectors at the end of Chapter 3.

In Chapter 4, a new PIC detector, namely APIC detector, is proposed and discussed in detail. The analytical and numerical results of bit error rate (BER) performance of the proposed detector are shown in varied conditions, such as perfect power control, near-far situation and multi-cell environment. In addition, its BER performance is compared with the other three detectors: conventional detector, BAMMSE detector and CPIC detector.

To improve the performance of the APIC detector in distorted channels, another novel PIC detector, namely ADFPIC detector, is proposed and analyzed thoroughly in Chapter 5. In this detector, a decision feedback scheme is proposed, where the data estimates after interference cancellation are employed to update the adaptive filters. In addition, the performance comparisons between the two proposed detectors (APIC and ADFPIC) and the other detectors are done in asynchronous channel and multipath Rayleigh fading channels.

Finally, Chapter 6 presents a retrospection of the whole thesis and gives recommendations for future work.

CHAPTER 2

DS-CDMA SYSTEMS

The DS-CDMA is the most popular of CDMA techniques. In DS-CDMA systems, the received signal is composed of the sum of all the users' signals, which overlap in time and frequency. The conventional detector for such systems detects each user separately without regard to the other users, and thus results in MAI, which limits the performance of DS-CDMA systems. In this chapter, we will discuss the background of DS-CDMA systems. We begin with a transmitter model for a specific user (k) followed by a K-user system model for DS-CDMA in Section 2.1 and continue with the properties of spreading codes in Section 2.2. We finish this chapter with the description of conventional detector and MAI effect.

2.1 System Model for DS-CDMA

In DS-CDMA transmitter, each user's signal is multiplied by its spreading code waveform, also known as signature waveform. Figure 2.1 depicts the DS-CDMA transmitter model for user k. Here, we select the binary phase shift keying (BPSK) digital modulation format for the transmitter.

Figure 2.1. DS-CDMA transmitter for the k^{th} user.

The k^{th} user transmits a signal of the form

$$s_k^p(t) = A_k b_k(t) g_k(t) \cos\left(w_c t + q_k\right). \tag{2.1}$$

The notation introduced in Eq.(2.1) are as follows:

- A_k is the signal amplitude
- w_c is the carrier frequency
- q_k is the carrier phase
- $b_k(t)$ is the information waveform and can be expressed as

$$b_k(t) = \sum_{l=-\infty}^{\infty} b_{k,l}\, p_{T_b}(t - lT_b), \tag{2.2}$$

where $\left\{b_{k,l}\right\}$ is a set of independent and identically distributed (*i.i.d.*) Bernoulli random variables. The symbol $b_{k,l}$ represents the l^{th} bit of k^{th} user taking values ± 1 with equal probability, T_b is the duration of the data bit and $p_{T_b}(t)$ is the unit rectangular pulse shaping function given by

$$p_{T_b}(t) = \begin{cases} 1, & 0 \le t < T_b \\ 0, & \text{otherwise.} \end{cases} \tag{2.3}$$

- $g_k(t)$ is the spreading code waveform which can be expressed as

$$g_k(t) = \sum_{n=-\infty}^{\infty} g_{k,n} p_{T_c}(t - nT_c) \,, \tag{2.4}$$

where $\{g_{k,n}\}$ is the binary spreading sequence and has the same distribution as $\{b_{k,l}\}$, T_c is the chip duration and $p_{T_c}(t)$ is the unit rectangular pulse shaping function similar to $p_{T_b}(t)$ with corresponding modifications. The chip rate f_c=1/T_c is much greater than the bit rate f_b=1/T_b. Thus, multiplying the BPSK signal at the transmitter by spreading code waveform has the effect of spreading it out in frequency by a factor f_c / f_b. This frequency spread factor is referred to as the processing gain (PG) or spreading gain and denoted as N [5], which reflects the degree of spectral spreading.

The DS-CDMA systems can be divided into short-code systems and long-code systems depending on the period of spreading code. If the period equals bit interval T_b, *i.e.*, the spreading code is same for each bit, it is called a short-code system, otherwise it is called a long-code system. In long-code system, the use of multiuser detection strategies becomes cumbersome [6, Chapter2]. Therefore, we concentrate on short-code system.

It is convenient to denote the transmitted signal in baseband model. Accordingly, the transmitted signal can be expressed as

$$s_k(t) = A_k b_k(t) g_k(t) \,. \tag{2.5}$$

As a result, a baseband equivalent model for a *K*-user DS-CDMA system is depicted in Figure 2.2. The model introduces finite, random propagation delay t_k (*k*=1,…,*K*) into the transmitted signal $s_k(t)$ producing $s_k(t-t_k)$ for each user, and corrupts the transmitted signal with AWGN, *w*(*t*), of power spectral density s^2. The channel is assumed to be memoryless here.

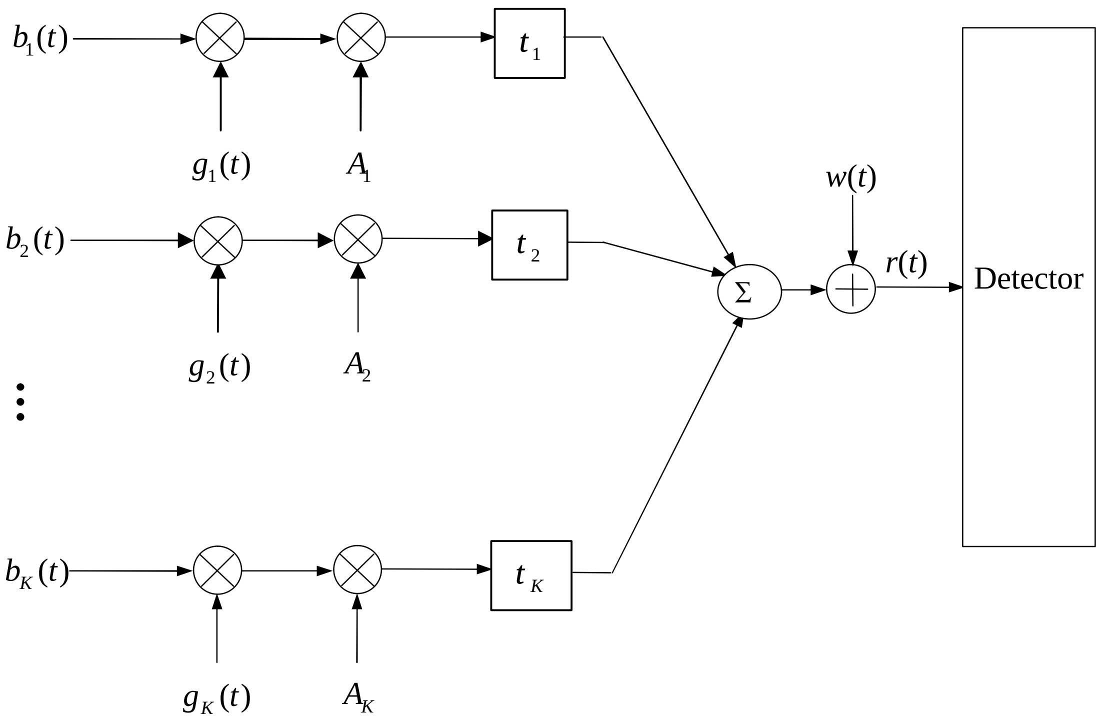

Figure 2.2. Equivalent baseband model for a DS-CDMA system.

The received signal *r*(*t*) is the sum of the delayed transmitted signals and the AWGN as shown below,

$$r(t) = \sum_{k=1}^{K} s_k(t-t_k) + w(t)$$

$$= \sum_{k=1}^{K} A_k b_k(t-t_k) g_k(t-t_k) + w(t) . \qquad (2.6)$$

For a synchronous system, all time delays can be set to zero without loss of generality (or $t_k = 0$ for $k = 1,..., K$), and hence Eq. (2.6) becomes

$$r(t) = \sum_{k=1}^{K} s_k(t) + w(t) = \sum_{k=1}^{K} A_k b_k(t) g_k(t) + w(t). \qquad (2.7)$$

2.2 Spreading Codes

Spreading codes play an important role in a DS-CDMA system as their characteristics directly impact the system performance. As mentioned in Chapter 1, the users in CDMA systems are distinguished by their spreading codes. The quality of the spreading codes is often gauged by their auto-correlation and cross-correlation properties. Optimally, the spreading codes should have auto-correlation functions that vanish everywhere except at zero delay, and cross-correlation functions that are identically equal to zero [17]. The degree to which code properties approach this, determines the degree to which users interfere with one another, and consequently, decides the system performance.

Maximum length sequences (or *m*-sequences) and Gold sequences are the most widely used spreading sequences in DS-CDMA systems. The *m*-sequences are generated using Linear Feedback Shift Register (LFSR). The generator polynomial governs all characteristics of the generator. It turns out that the sequence generated by a *primitive polynomial* is an *m*-sequence [18], which has the maximum possible period for a given stage shift register. The *m*-sequences have three important properties: (i) balance property, (ii) run-length property, and (iii) the shift-and-add property. Because of the first and third properties, the *m*-sequences have excellent auto-correlation property.

However, their cross-correlation property is relatively poor compared to Gold codes. The generation of Gold codes is very simple. Using a *preferred pair* of *m*-sequences (say u and v) of the same degree r, the Gold codes can be generated by taking the modulo-2 sum of u with the N cyclically shifted versions of v. As a result, 2^r+1 Gold codes are available [19]. Cross-correlations of any pair in this set has taken on one of the three values (for any lap) $\left\{-\frac{1}{N}, -\frac{1}{N}t(r), \frac{1}{N}\left[t(r)-2\right]\right\}$, where

$$t(r) = \begin{cases} 2^{(r+1)/2}+1, & \text{for odd value of } r \\ 2^{(r+2)/2}+1, & \text{for even value of } r. \end{cases} \tag{2.8}$$

Here N is the spreading gain with $N=2^r-1$.

For the simple generation procedure and relatively good correlation properties of Gold codes, we will use them as the spreading codes in this thesis.

2.3 Conventional Detector for DS-CDMA Systems

The conventional DS-CDMA detector follows a single-user detection strategy, *i.e.*, it detects one user without regard to the existence of the other users. Consequently, it suffers from the MAI, which refers to the interference between direct-sequence users. In this section, we take a detailed look at the conventional detector and the effect of MAI.

In a conventional DS-CDMA system, a particular user's signal is detected by correlating the entire received signal with that user's spreading code waveform. We begin the analysis with a synchronous case and the channel here is assumed to be memoryless. As shown in Figure 2.3, the conventional detector is a bank of K matched filters (MF), thus the conventional detector is referred to as the MF detector. The MF bank uses one MF to detect one user's signal. Each user's spreading code is correlated with the received signal in a separate detector branch. The outputs of the filters are sampled at bit rate, which yields "soft" estimates z_k (k=1,…,K) of the transmitted data. The final "hard" data estimates $\hat{b}_k$ (k=1,…,K) are made according to the signs of the soft estimates as

$$\hat{b}_k = \mathrm{sgn}(z_k)\,, \tag{2.9}$$

where $\mathrm{sgn}(.)$ denotes the signum function and is given by

$$\mathrm{sgn}(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0. \end{cases} \tag{2.10}$$

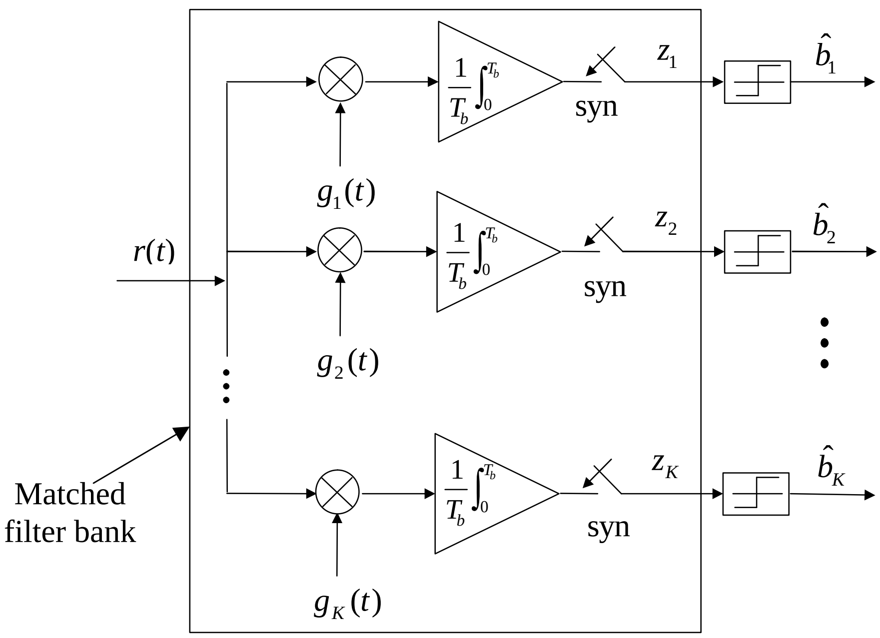

Figure 2.3. Conventional DS-CDMA detector.

As it is obvious from Figure 2.3, the conventional detector follows a single-user detector strategy; each branch detects one user without regard to the existence of the other users. The output of the k^{th} branch (for k^{th} user) for a particular bit interval is,

$$
\begin{aligned}
z_k &= \frac{1}{T_b}\int_0^{T_b} r(t)g_k(t)dt \\
&= r_{kk}A_k b_k + \sum_{i=1, i\neq k}^{K} r_{ik}A_i b_i + \frac{1}{T_b}\int_0^{T_b} w(t)g_k(t)dt \\
&= A_k b_k + \mathrm{MAI}_k + w_k, \qquad (2.11)
\end{aligned}
$$

where $r_{ik} = \frac{1}{T_b}\int_0^{T_b} g_i(t)g_k(t)dt$ is the correlation between spreading codes (corresponding to users i and k). It refers to the auto-correlation when $i = k$, cross-correlation when $i \neq k$, and we assume that the auto-correlation $r_{kk} = 1$. w_k is the noise, which is a Gaussian random variable with zero mean and variance equal to s^2/N. As shown in Eq. (2.11), the correlation of the spreading code with the signal of k^{th} user itself produces the desired data term (first term), the correlation with all the other users produces MAI (second term), and the correlation with the noise yields the noise term (third term) [5].

The outputs of all K users for a bit can be expressed in a simple matrix-vector format as shown below:

$$\mathbf{z} = \mathbf{RAb} + \mathbf{w}, \qquad (2.12)$$

where the vectors **z**, **b** and **w** are output of the MF bank, the transmitted bits and the noise with covariance matrix equal to $s^2\mathbf{R}/N$, respectively. There are K elements in each vector. Matrix **A** is a diagonal $K \times K$ matrix containing the corresponding received amplitudes (**A**=diag $[A_1,\ldots,A_K]$). Matrix **R** is a $K \times K$ correlation matrix, whose entries contain the values of the correlations between every pair of codes (the $(i,k)^{\text{th}}$ element of **R** is $\mathbf{R}_{ik}= r_{ik}$; $i, k=1,\ldots,K$).

In a general asynchronous system, *i.e.*, the received signal is in the form of Eq. (2.6). In this case, the matrix-vector model can take the same form as Eq. (2.12). However, the equation must encompass the entire message for all bits. In synchronous channel, since the bits of each user are aligned in time, detection can focus on one bit interval independent of the others. On the other hand, in asynchronous channel, there is overlap between bits of different intervals, and therefore any decisions made on a particular bit of one user needs to take into account the decisions on the overlapping bits of the other users. As a result, the detection problem must be framed over the whole message [20]. Assuming there are L bits per user, the size of the vectors and the order of the matrices in Eq. (2.12) becomes LK. The vectors **z**, **b** and **w** are the matched filter bank output, data and noise, respectively, for all L bit intervals. Matrix **A** contains the corresponding received amplitudes. The matrix **R** now contains the partial correlations of every pair of the LK code words and can be represented by [6]:

$$\mathbf{R} = \begin{bmatrix} \mathbf{R}(0) & \mathbf{R}^T(1) & 0 & \cdots & \cdots \\ \mathbf{R}(1) & \mathbf{R}(0) & \mathbf{R}^T(1) & 0 & \cdots \\ 0 & \ddots & \ddots & \ddots & 0 \\ \cdots & 0 & \mathbf{R}(1) & \mathbf{R}(0) & \mathbf{R}^T(1) \\ \cdots & \cdots & 0 & \mathbf{R}(1) & \mathbf{R}(0) \end{bmatrix}. \tag{2.13}$$

where the $K \times K$ matrices $\mathbf{R}(0)$ and $\mathbf{R}(1)$ are defined by

$$[\mathbf{R}(0)]_{ik} = \begin{cases} r_{ik}, & i < k \\ r_{ki}, & i > k \\ 1, & i = k, \end{cases}$$

and

$$[\mathbf{R}(1)]_{ik} = \begin{cases} r_{ki}, & i < k \\ 0, & i \geq k. \end{cases} \tag{2.14}$$

Here r_{ik} is the partial correlation between user *i* and *k* in asynchronous channel, which is different from that in Eq. (2.11) and can be denoted as (if *i*<*k*),

$$r_{ik} = \frac{1}{T_b} \int_{t}^{T_b} g_i(t) g_k(t - t) dt,$$

and

$$r_{ki} = \frac{1}{T_b} \int_{0}^{t} g_i(t) g_k(t + T_b - t) dt, \tag{2.15}$$

with $t = t_k - t_i$. Here we assume, without loss of generality, that the users are labeled so that their delays are increasing, *i.e.*, $t_1 < t_2 < ... < t_K$.

Based on the above analysis, the success of the conventional detector depends on the properties of the correlation between spreading codes. In synchronous channel, MAI would be completely removed if the spreading codes are mutually orthogonal, *i.e.*, **R=I** (an identity matrix) or $r_{ik} = 0$, for i, $k = 1, ..., K$ and $i \neq k$. However, this is an ideal situation, and only spreading codes with near-ideal properties (mutual correlation as small as possible) can be achieved, such as Gold codes. Moreover, in asynchronous channel, it is impossible to design codes which can maintain orthogonality over all possible delays. Consequently, MAI exists as a result of the imperfect orthogonality of spreading codes and the asynchronous reception of the users' signals. The existence of MAI limits the capacity and performance of the conventional DS-CDMA systems. As the number of interfering users increases, the amount of MAI increases. In addition, the overall effect of MAI on system performance is even more pronounced if the users' signals arrive at the receiver at different powers: weaker users (small-amplitude) may be overwhelmed by stronger users (large-amplitude). Such a situation arises when the transmitter have different geographical locations relative to the receiver; the signals of the closer transmitting users undergo less amplitude attenuation than the signals of users that are further away. This is the well known near-far problem [5]. Some methods have been proposed to mitigate the effect of MAI, such as power control [21], looking for codes that are nearly orthogonal [22] etc. Among them, multiuser detection is a promising strategy, which will be discussed in the next chapter.

2.4 Concluding Remarks

This chapter has introduced the system model for a DS-CDMA system, and discussed the properties of the spreading codes, which are crucial for the performance of the systems. Conventional detector for such systems has been discussed in detail. Also, the effect of MAI and near-far problems, introduced by the conventional detector, has been discussed in this chapter.

CHAPTER 3

OVERVIEW OF MULTIUSER DETECTION SCHEMES

Conventional DS-CDMA detector suffers from MAI and near-far problems, which were discussed in the previous chapter. Multiuser detection is a signal processing technique used to overcome these limitations and improve the capacity and performance of DS-CDMA communication systems. The optimal multiuser detector is too complex for practical application although it offers excellent performance. Therefore, a great effort has been focused on finding suboptimal detectors. In this chapter, the optimal multiuser detector is briefly introduced in Section 3.1. In Section 3.2, several important sub-optimal multiuser detection schemes reported in the literature are reviewed. In addition, the idea of combining PIC detectors with linear schemes for improved performance is discussed in Section 3.4.

3.1 Optimal Multiuser Detection

The optimal maximum likelihood detector was proposed by Verdu in 1986 [6,23]. It comprises the matched filter bank, followed by a Viterbi decision algorithm. This detector is shown to have significant performance improvement over the conventional detector and is near-far resistant. The structure of optimal detector is different from the conventional one by including a Viterbi decision algorithm. This led to the conclusion that whether a detector is effective in the presence of MAI and near-far problems is depend on the structure of the detector.

The major problem with this optimal detector is the prohibitively expensive complexity. The Viterbi decision algorithm in the detector performs MLS estimation over the entire sequence of received message bits, thereby decoding the whole message sequence in a trellis with 2^K stages (K is the number of users). The computational complexity per bit decision then becomes exponential with the number of users. A realistic DS-CDMA system has a relatively large number of active users; thus the exponential complexity in the number of users makes the cost of this detector too high.

Despite the huge performance and capacity gains over conventional detection, the optimal detector is not practical because of the reasons stated above. Sub-optimal approaches are thus sought, which exhibit more reasonable computational complexity. Most of these approaches fall into two broad categories: (i) linear multiuser detectors and (ii) subtractive interference cancellation detectors. Some of them are discussed in the subsequent sections of this chapter.

3.2 Linear Detection

The most fundamental group of suboptimal detectors is linear detectors [7]. These detectors apply a linear transform **L** to the soft output of the conventional detector to reduce the MAI seen by each user. Two of the most cited linear multiuser detectors are the decorrelating detector and the MMSE detector [20,24,25].

3.2.1 Decorrelating Detector

The block schematic of decorrelating detector [20,24] is shown in Figure 3.1. It removes all cross correlations between users by selecting the linear transform as the inverse of the spreading code correlation matrix as follows:

$$\mathbf{L}_{\text{dec}} = \mathbf{R}^{-1}. \tag{3.1}$$

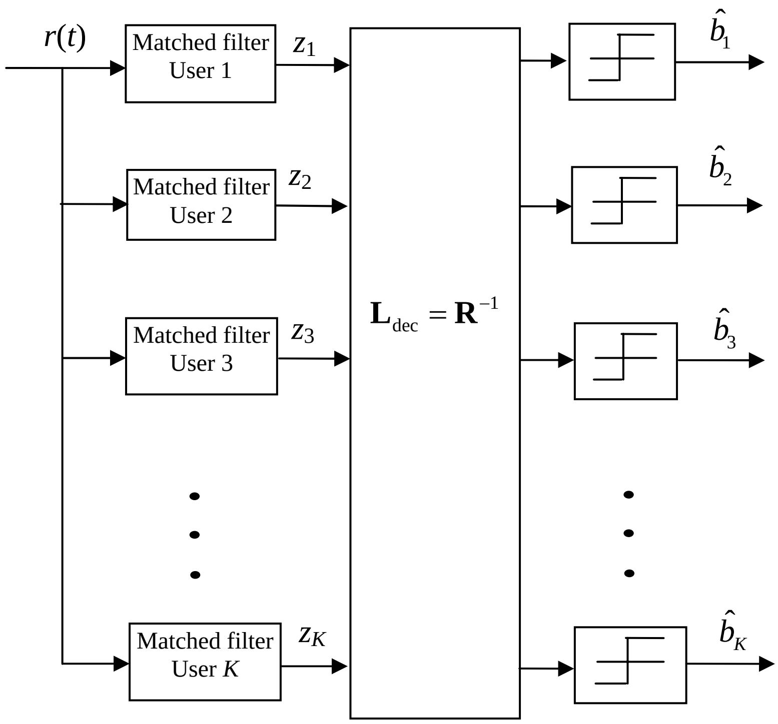

Figure 3.1. Structure of the decorrelating detector.

After applying the linear transform, $\mathbf{L}_{\text{dec}}$ to the soft output of the conventional detector, $\mathbf{z}$ (shown in Eq. (2.12)), the data estimates of the decorrelating detector are given by

$$\hat{\mathbf{b}} = \text{sgn}(\mathbf{R}^{-1}\mathbf{z}) = \text{sgn}(\mathbf{A}\mathbf{b} + \mathbf{R}^{-1}\mathbf{w}) = \text{sgn}(\mathbf{A}\mathbf{b} + \mathbf{w}_{\text{dec}}), \tag{3.2}$$

where $\mathbf{R}$, $\mathbf{A}$, $\mathbf{z}$, $\mathbf{b}$ and $\mathbf{w}$ are already described in Eq. (2.12). The vector $\mathbf{w}_{\text{dec}}$ is the noise term at the output of the decorrelating detector. The decision variable $\hat{\mathbf{b}}$ consists of just the decoupled data plus a noise term. Thus, the decorrelating detector completely eliminates MAI. This detector offers many desirable features, e.g., it yields an optimal value of near-far resistance performance metric and does not need to estimate the received signal amplitude.

Though the decorrelating detector has certain advantages, it has several drawbacks. One drawback of the decorrelator is that it leads to noise enhancement. The power of noise term $\mathbf{w}_{\text{dec}}$ in Eq.(3.2) is always greater than or equal to the power associated with the noise term at the output of the conventional detector ($\mathbf{w}$ in Eq. (2.12)) [5,20]. A more significant disadvantage is that the matrix inversion $\mathbf{R}^{-1}$ needs to be performed, which is a computationally intensive ($O(K^3)$) operation. This is especially cumbersome in asynchronous DS-CDMA systems, where the size of the matrix $\mathbf{R}$ is significantly high and thus entails more computation for inversion. Further, the decorrelator relies upon accurate spreading code correlation values, and if the inverse correlation matrix becomes unstable or undefined even, then the detector ceases to function adequately. Because of all these disadvantages, the linear decorrelator is not commonly used.

3.2.2 MMSE Detector

Another popular linear detector is the MMSE detector [25]. The block schematic of such a detector is shown in Figure 3.2. Unlike the linear decorrelator, the MMSE detector takes into account the background noise and utilizes the knowledge of the received signal powers. This detector implements a linear transform $\mathbf{L}_{\mathrm{MMSE}}$ to minimize the cost function, which is the mean-squared error (MSE) between the transmitted bit and the soft output of the MMSE detector as described below

$$J(\mathbf{L}_{\mathrm{MMSE}}) = E\left\|\mathbf{b} - \mathbf{L}_{\mathrm{MMSE}}\mathbf{z}\right\|^2 , \tag{3.3}$$

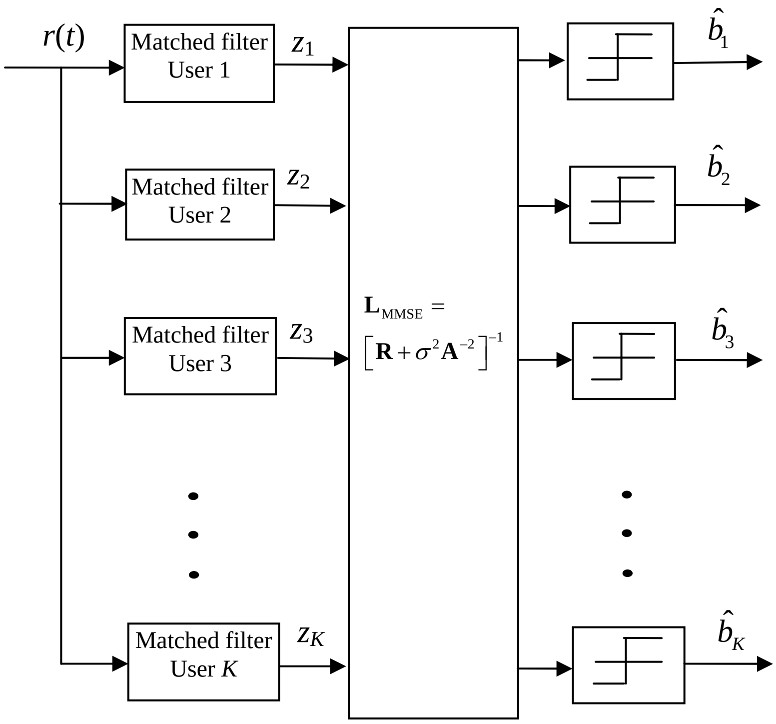

Figure 3.2. Structure of the MMSE detector.

where $\mathbf{z}$ is soft output of the conventional detector (shown in Eq. (2.12)) and thus results in the linear transform as

$$\mathbf{L}_{\text{MMSE}} = \mathbf{A}^{-1}\left[\mathbf{R} + \sigma^2\mathbf{A}^{-2}\right]^{-1},$$

$$\mathbf{L}_{\text{MMSE}} \triangleq \left[\mathbf{R} + \sigma^2\mathbf{A}^{-2}\right]^{-1}. \tag{3.4}$$

where $\mathbf{R}$, $\mathbf{A}$ and σ^2 are already described in Eq. (2.12). $\mathbf{L}_{\text{MMSE}}$ is finally equivalent to $\left[\mathbf{R} + \sigma^2\mathbf{A}^{-2}\right]^{-1}$ because it is enough for detection purpose, and $\mathbf{A}$ is positive definite. Applying the linear transform $\mathbf{L}_{\text{MMSE}}$ to $\mathbf{z}$, the data estimates of the MMSE detector are given by

$$\hat{\mathbf{b}} = \text{sgn}(\mathbf{L}_{\text{MMSE}}\mathbf{z})\ . \tag{3.5}$$

As can be seen in Eq. (3.4), the MMSE detector implements a partial inverse of the correlation matrix. It balances the desire to completely eliminate MAI with the desire not to enhance the background noise. Therefore, the MMSE detector generally provides better BER performance than the decorrelating detector. And as the background noise goes to zero, the MMSE detector converges in performance to that of the linear decorrelating detector.

This detector also has some disadvantages. One disadvantage is that it requires estimation of received amplitudes as is clear from Eq. (3.4). Another important disadvantage is that its performance depends on the powers of the interfering users, thereby causing decreased near-far resistance. In addition, the detector also faces the computationally intensive task of matrix inversion.

3.2.3 Adaptive MMSE Detector

In general, linear detectors provide substantial performance and capacity gains over the conventional detector. However, both decorrelating and MMSE detectors have the problem of calculating the matrix inversion, which is too expensive. There have been many suboptimal approaches to implementing these two detectors in order to reduce the computational complexity [26-28]. However, the computational requirement is still substantial, especially for asynchronous channel and/or high system load. An alternative approach is the adaptive implementation of the decorrelating detector [29] and MMSE detector [9,13]. Adaptive multiuser detectors are very useful because they can adapt to unknown and time varying channel parameters and reduce the computational complexity in the mean time. The MMSE detector is more attractive for adaptive implementation because of its natural link to adaptive filtering techniques, which is well understood [12]. Therefore, we concentrate on the adaptive MMSE detector.

The adaptive MMSE detector is proposed in [9] and analyzed in [13]. The structure of the scheme is shown in Figure 3.3. The baseband received signal $r(t)$ (as in Eq. (2.6)) is passed through a chip matched filter and sampled at the end of every chip interval. These samples are fed into the adaptive equalizer which is implemented as an adaptive finite-impulse-response (FIR) digital filter. This filter for the k^{th} user is shown in Figure 3.3 as an equivalent tapped delay line (TDL) for ease of discussion. The output of the equalizer is sampled once every bit interval. Then, according to the sign of this sample value, the data estimate $\hat{b}_k$ is formed. Here we note that the input to the filter is clocked at chip rate, while the output is clocked at the bit rate as opposed to traditional equalization techniques where the output is sampled at the same rate as the input.

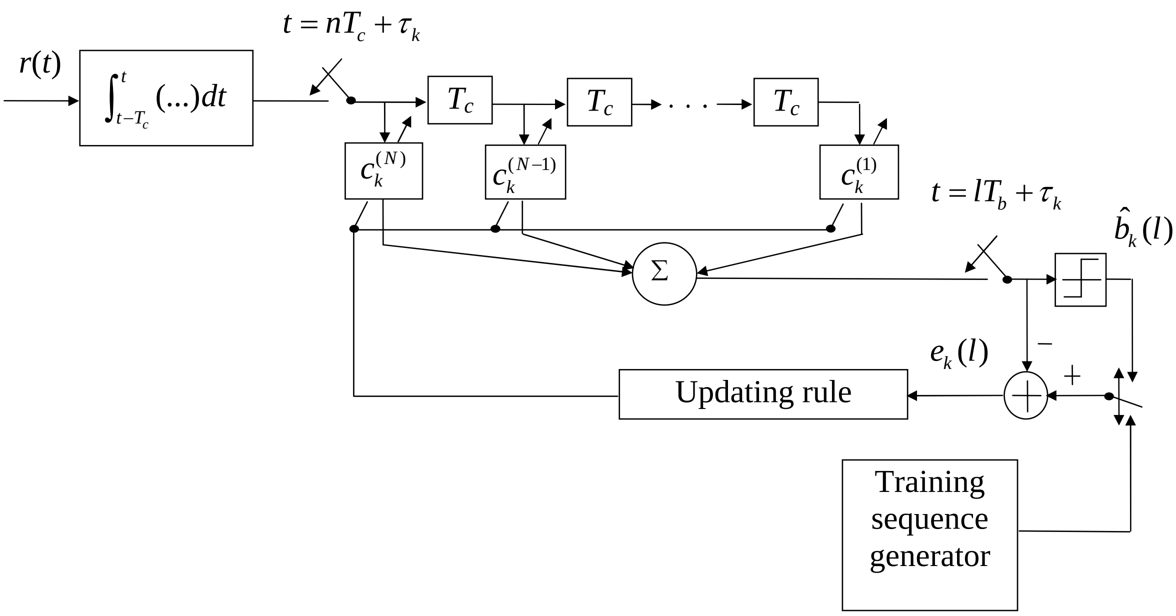

Figure 3.3. Structure of the adaptive MMSE detector for the k^{th} user.

If the weights of the TDL were taken to be the elements of the spreading code of the corresponding user, this detector would be equivalent to the conventional detector. In the presence of MAI, this detector will update the tap weights once every bit interval and adjust them to a form which is optimum for the prevailing interference and noise.

LMS and RLS are two popular algorithms for adaptive implementation of the MMSE detector. The former has a lower computational complexity, while the latter has a faster convergence rate and lower steady state error, at the expense of higher computational complexity and numerical instability. The updating rule using LMS algorithm for adjusting the tap weights is given by

$$\mathbf{c}_k(l+1) = \mathbf{c}_k(l) + \mu e_k(l)\mathbf{r}_k(l)\,, \tag{3.6}$$

where $\mathbf{r}_k(l)$ represents the vector of N samples of the chip matched filter output (sampled at chip rate and time aligned to the k^{th} user, $t = nT_c + \tau_k$) over l^{th} bit duration, $\mathbf{c}_k(l) = \left[c_k^{(1)}(l), \ldots, c_k^{(N)}(l)\right]^T$ is the vector of tap weights after $(l\text{-}1)^{\text{th}}$ update, $e_k(l) = b_k(l) - \mathbf{c}_k{}^T(l)\mathbf{r}_k(l)$ is the estimation error for the k^{th} user, and μ is the convergence parameter satisfying $0 < \mu < \dfrac{2}{\lambda_{\max}}$ to ensure convergence [12]. Here, $\lambda_{\max}$ is the largest eigenvalue of the correlation matrix of $\mathbf{r}_k(l)$. Generally, a large μ leads to a faster convergence rate, however it will also cause a greater gradient noise.

The updating rule using RLS algorithm for adjusting the tap weights is given by

$$\mathbf{c}_k(l+1) = \mathbf{c}_k(l) + \mathbf{P}(l)\mathbf{r}_k(l)e_k(l)\,,$$

$$\mathbf{P}(l+1) = \rho^{-1}\left[\mathbf{P}(l) - \frac{\mathbf{P}(l)\mathbf{r}_k(l)\mathbf{r}_k{}^T(l)\mathbf{P}(l)}{\rho + \mathbf{r}_k{}^T(l)\mathbf{P}(l)\mathbf{r}_k(l)}\right], \tag{3.7}$$

where $\mathbf{P}(0) = \delta^2\mathbf{I}$, δ is a large positive constant, ρ $(0 \ll \rho \le 1)$ is the weighting factor, which is used to "forget" the data samples in distant past, and $(.)^T$ means the transpose operator.

3.3 Subtractive Interference Cancellation

Another important group of multiuser detectors can be classified as subtractive interference cancellation detectors. The basic principle underlying these detectors is to estimate and then subtract the interference seen by each user. These detectors may be implemented with variable number of stages. The interference cancellation detectors can utilize either soft decision (SD) or hard decision (HD) of the data estimates in forming the MAI estimate [5] and the HD is assumed here. We will review two subtractive interference cancellation detectors below.

3.3.1 Successive Interference Cancellation

The successive interference cancellation (SIC) detector takes a serial approach to interference cancellation [14,15]. In each stage, this detector regenerates and cancels one additional user from the received signal, so that the remaining users see less MAI in the next stage. The performance of this detector can be improved by canceling the users' signal from the strongest to the weakest according to their power. The SIC detector is thus preceded by a stage which ranks users in descending order of received power. As a result, the strongest user will not benefit from any MAI reduction; while the weakest users will see a huge reduction in their MAI.

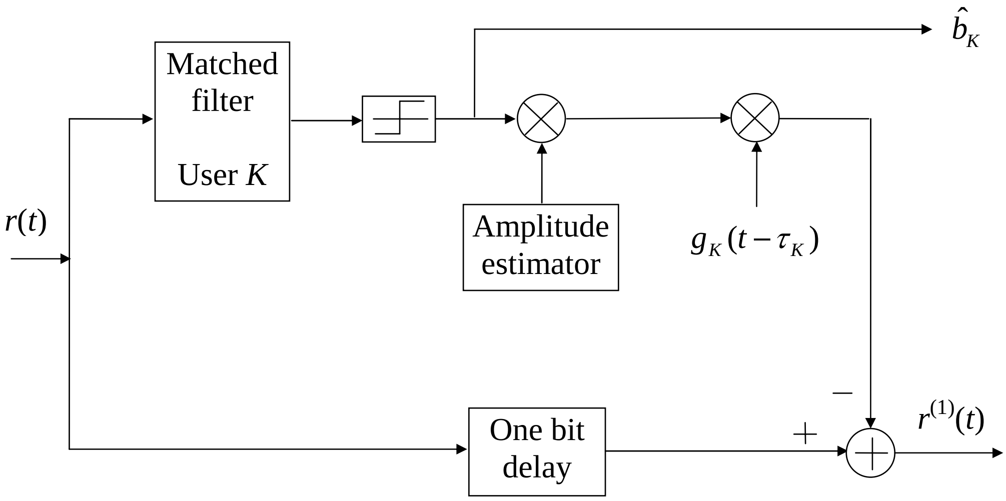

Figure 3.4. The first stage of the SIC detector (HD).

A simplified diagram of the first stage of this detector is shown in Figure 3.4. First, it produces a hard data estimate of the strongest user (we assume the K^{th} user as the strongest one). By using this data estimate, knowledge of spreading code and estimates of timing and amplitude, the detector regenerates an estimate of the received signal of this user. It then subtracts this regenerated signal from the total received signal $r(t)$ (as in Eq. (2.6)), thereby yielding a interference-supressed signal $r^{(1)}(t)$. Here superscript '(1)' stands for stage 1. Assuming that the estimation is correct, the outputs of stage 1 are a modified received signal without the MAI caused by the strongest user and a data estimate for the strongest user. This process can be repeated in a multi-stage structure. At the m^{th} stage, the input is the output from the previous stage, $r^{(m\text{-}1)}(t)$, and the outputs are a received signal $r^{(m)}(t)$ with less MAI and one additional data estimate.

The SIC detector requires only a minimal amount of additional complexity ($O(K)$) compared to conventional detector [5]. However, there are some problems with this detector. First, an additional bit delay is required to cancel one user. When the number of users is large, the excessive delay will become unacceptable. Second, there is a need to reorder the signals whenever the power profile changes. Third, if a bit estimate is wrong, the interfering effect of that bit on the output signal to noise ratio (SNR) is quadrupled in power. Thus, it is crucial that the data estimates of at least the strongest users be reliable.

3.3.2 Parallel Interference Cancellation

An alternative to SIC is the parallel interference cancellation (PIC) detector, which carries out the interference cancellation in parallel. The multistage PIC structure was introduced in [16]. A basic one stage PIC structure is assumed in [15,30].

In the multistage conventional PIC (CPIC) detector, the data estimates are derived from MF detectors. At the initial stage, the data estimates $\hat{b}_k^{(0)}$, k=1,…,K, for a particular bit interval are achieved as

$$\hat{b}_k^{(0)} = \mathrm{sgn}(z_k^{(0)}); \qquad k=1,\ldots,K \tag{3.8}$$

where

$$\begin{aligned} z_k^{(0)} &= \frac{1}{T_b}\int_{\tau_k}^{T_b+\tau_k} r(t)g_k(t-\tau_k)dt \\ &= A_k b_k + \sum_{i=1,i\neq k}^{K} \frac{1}{T_b}\int_{\tau_k}^{T_b+\tau_k} s_i(t-\tau_i)g_k(t-\tau_k)dt + \frac{1}{T_b}\int_{\tau_k}^{T_b+\tau_k} w(t)g_k(t-\tau_k)dt, \end{aligned} \tag{3.9}$$

and $r(t)$ is described in Eq. (2.6). The second term in the right hand side of Eq.(3.9) is the MAI.

At the m^{th} stage, the estimated data signals from the $(m\text{-}1)^{\text{th}}$ stage are scaled by amplitude estimates and re-spread by the codes, which produces a regenerated signal $\hat{s}_k^{(m-1)}(t)$ for each user. Based on the regenerated signals, the interference estimate for each user can be obtained. Assuming perfect amplitude and delay estimation, the result after subtracting the interference estimate for user k ($\hat{I}_k^{(m)}(t)$) from the received signal is

$$r_k^{(m)}(t) = r(t) - \hat{I}_k^{(m)}(t) = r(t) - \sum_{i=1, i\neq k}^{K} \hat{s}_i^{(m-1)}(t-\tau_i)\,, \tag{3.10}$$

where the regenerated signals of other users are represented by

$$\hat{s}_i^{(m-1)}(t) = A_i g_i(t) \sum_{l=-\infty}^{\infty} \hat{b}_i^{(m-1)}(l)\, p_{T_b}(t-lT_b)\,, \tag{3.11}$$

and $p_{T_b}(t-lT_b)$ is the rectangular pulse shaping function as in Eq. (2.3). Then, the interference-suppressed signals $r_k^{(m)}(t)$ (k=1,…,K) are passed on to next set of MF bank to produce a new and hopefully better set of data estimates.

In general, PIC has a slightly higher complexity than SIC [31], while it causes much less delay compared to SIC, *i.e.*, its cancellation process is much faster than the successive canceller. However, there are some disadvantages for PIC schemes. Similar to SIC, PIC needs a priori knowledge of signal amplitudes and delays. The performance of PIC detector also depends on the accuracy of data estimates, especially, the initial data estimates. Therefore, several methods which try to increase the accuracy of the data estimates in PIC have been proposed and this topic will be discussed in next section.

3.4 PIC Scheme Based on the Linear Detector

Based on the discussion of multiuser detection, subtractive interference cancellers are much simpler than linear multiuser detectors and they can achieve performance enhancements if the data estimates are accurate. Therefore, interference cancellation has received a great deal of attention and has been suggested as one of the most promising multiuser detection schemes [32]. Considering the advantages of PIC over SIC, we will focus our study on PIC schemes.

PIC is designed to cancel the interference estimate, and therefore, it has the potential for further performance improvement if this estimate is more accurate. As shown in [33], if the data of all interfering users are known a priori, the optimum decision for the desired user can be achieved in the sense of maximum-likelihood (ML). In PIC, the exact knowledge of the interfering bits is unknown and hence, their estimates are used instead. As shown in Eq.(3.11), at the m^{th} stage, the detector uses the data estimates from the $(m\text{-}1)^{th}$ stage. As the estimates from the previous stages improve, the performance of the multistage PIC is improved as a result. In the CPIC detector, discussed in Section 3.3.2, the data estimates in each stage are derived from the MFs. To improve the accuracy of the data estimates, the MFs in CPIC are replaced by linear detectors such as decorrelating detector and MMSE detector, and are reported elsewhere [5,34,35]. These schemes are shown to have better performance than the CPIC detector. This is due to the fact that the linear detectors significantly outperform the conventional detector. Motivated by this idea, two novel multiuser detection schemes are proposed in this thesis, which are PIC detectors based on simple blind adaptive MMSE detection. In the following two chapters, we will analyze these two schemes in detail.

3.5 Concluding Remarks

This chapter has reviewed some important multiuser detection schemes reported in the literature. First, the optimal multiuser detector is discussed briefly along with its merits and demerits. Then, some suboptimal detectors are introduced and their advantages and disadvantages are discussed. In general, linear detectors have significant performance improvement over the conventional detector. However, they require nontrivial computation of the inverse of the correlation matrix. These shortcomings have provided motivation to develop adaptive implementations of linear detectors. Among them, adaptive MMSE detector is the most popular one. Subtractive interference cancellation detectors have much less complexity compared to the linear detectors and have relatively good performance. However their performance depends on the data estimates. PIC has the potential of performance improvement if the data estimates from the previous stages are accurate. To achieve better performance of PIC, we can introduce the linear detectors into the PIC. And this topic has been discussed at the end of this chapter.

CHAPTER 4

PIC SCHEME BASED ON ADAPTIVE MMSE DETECTOR

The capacity and performance of DS-CDMA systems is limited by the MAI and the near-far problem. Many multiuser detection schemes were proposed to mitigate these problems. Among them, PIC is one of the promising detectors. In recent years, PIC has drawn a lot of interests, and studies on PIC for DS-CDMA systems have gone so far as an experimental evaluation phase. One of the most advanced work can be seen in [36]. PIC has low complexity and the potential to combat the near-far problem, since it is designed to cancel interference. However, its performance is dependent on the accuracy of the data estimates. In the conventional PIC (CPIC) [16], MFs are used for data estimation, which are sensitive to near-far problem. Therefore, the potential of PIC is limited. In addition, CPIC requires the information of all users involved in the received signal for complete interference cancellation. Consequently, in multi-cell environment, it cannot suppress the interference from other cells (inter-cell interference) since the base station contains the information of users only in its own cell.

On the other hand, adaptive MMMSE detector [9,13] is shown to have much improved performance over the conventional detector. Also the adaptive nature of the detector allows it to learn the required information and adjust itself to the prevailing interference and noise environment. As a result, it can suppress the interference from the other cells (inter-cell interference) without the exact knowledge of the interferers.

Taking into account the attributes of PIC and adaptive MMSE detectors, a new multiuser detector is presented in this chapter. It exploits the advantages of the two detectors by combining a simple blind adaptive MMSE (BAMMSE) detector with the PIC. In the proposed adaptive PIC (APIC) scheme, BAMMSE detectors are used for data estimation in each stage instead of MFs. The remainder of the chapter is organized as follows. The system model is described in the next section. Because the APIC scheme is related to the MF, MMSE, CPIC detectors, the theoretical performances of these three fundamental multiuser detectors are analyzed in Section 4.2. The APIC scheme is discussed in detail in Section 4.3. This section also includes the performance analysis in multi-cell environment. In Section 4.4, the simulation results of this scheme are presented along with the theoretical results for perfect power control case, near-far channels and multi-cell environment. Finally, the last section summarizes the chapter with some concluding remarks.

4.1 System Model

Assuming there are K direct-sequence users in a DS-CDMA system, the baseband received signal can be expressed as

$$r(t) = \sum_{k=1}^{K} s_k(t) + w(t)$$

$$= \sum_{k=1}^{K} A_k b_k(t) g_k(t) + w(t). \tag{4.1}$$

The transmitted data $b_k(t)$ has bit duration T_b, the spreading code waveform $g_k(t)$ has duration T_c and $T_b=NT_c$, where N is the spreading gain. $w(t)$ is the AWGN with power spectral density σ^2.

To illustrate our scheme, the received signal $r(t)$ is passed through a chip matched filter, which can ensure that $r(t)$ is within a bandwidth $\left[-\frac{1}{2T_c}, \frac{1}{2T_c}\right]$, and then sampled at chip interval $t=nT_c$. The discrete model can be written as:

$$r(n) = \sum_{k=1}^{K} A_k b_k\left(\lfloor n/N \rfloor\right) g_k(n) + w(n). \tag{4.2}$$

Here $r(n) \triangleq r(nT_c)$, $g_k(n) \triangleq g_k(nT_c)$, $w(n) \triangleq w(nT_c)$ and $\lfloor n/N \rfloor$ denotes the smallest integer greater than the ratio n/N. In the following analysis, the dependence of b_k on the symbol index will be omitted for convenience.

Without loss of generality, we assume the first user (k=1) as the user of interest. Then, Eq. (4.2) can be modified as

$$\begin{aligned} r(n) &= A_1 b_1 g_1(n) + \sum_{k=2}^{K} A_k b_k g_k(n) + w(n) \\ &= A_1 b_1 g_1(n) + I_1(n) + w(n). \end{aligned} \tag{4.3}$$

Here, $I_1(n)$ is the interference to the first user contributed by the other users.

In order to accomplish the MAI cancellation and data detection effectively, it is necessary to have the estimates of the signal attenuation and delay. In the following discussion, as in previous papers dealing with multiuser detection approaches [37], we assume a perfect knowledge of these parameters at the detectors.

4.2 Performance Analysis

In this section, we analyze three well known multiuser detectors, *i.e.*, MF, MMSE and PIC detectors. The BER expression for each detector is presented.

4.2.1 MF Detector

MF detector consists of a bank of filters as shown in Figure 2.3. Each branch of the MF bank consists of the correlation operation of the received signal with one particular user's spreading code. The soft estimate (or decision statistic) of the user of interest (user 1) can be expressed as follows:

$$\begin{aligned} z_1 &= \frac{1}{N}\left[\sum_{n=1}^{N} r(n) g_1(n)\right] \\ &= A_1 b_1 \rho_{11} + \sum_{k=2}^{K} \rho_{1,k} A_k b_k + \frac{1}{N}\left[\sum_{n=1}^{N} w(n) g_1(n)\right] \\ &= A_1 b_1 + \mathrm{MAI}_1 + w_1, \end{aligned} \tag{4.4}$$

where $\rho_{1k} = \frac{1}{N}\left[\sum_{n=1}^{N} g_1(n) g_k(n)\right]$ is the correlation between the spreading code of the first user and k^{th} user. When k=1, $\rho_{11} = \frac{1}{N}\left[\sum_{n=1}^{N} g_1(n) g_1(n)\right] = 1$ is the autocorrelation of the first user. MAI_1 is the MAI to the first user contributed by the other users and w_1 is the noise part of the first user.

If the number of users is relatively large and the powers of the interfering signals are similar, the central limit theorem can be applied to assume MAI_1 to be Gaussian distributed. Then, the sum of MAI_1 and w_1 (noise term) can be treated as Gaussian noise, because they are independent. This Gaussian variable is represented as *y*. The mean and variance of *y* can be calculated and the results are: $E[y]=0$ and $var[y]=\sum_{k=2}^{K} A_k^2\rho_{1k}^2+\frac{\sigma^2}{N}$.

As a result, the BER of the MF detector can be represented as [6]:

$$\mathrm{BER}_{\mathrm{MF}}=Q\left(\sqrt{\frac{A_1^2}{\frac{\sigma^2}{N}+\sum_{k=2}^{K}A_k^2\rho_{1k}^2}}\right), \tag{4.5}$$

where *Q*(.) is the standard *Q*–function, $Q(x)=\int_x^{\infty}\frac{1}{\sqrt{(2\pi)}}e^{-t^2/2}dt$. This approximation is generally good at low SNR; for high SNR, it may be unreliable. This is due to the fact that, at low SNR, the background Gaussian noise w_1 is relatively large and thus is dominant in the whole noise part (the sum of MAI_1 and w_1). As a result, the approximation of the whole noise part as Gaussian distributed is good in this condition. For very high SNR, MAI_1 is dominant in the noise part, and thus the accuracy of the approximation is dependent on whether MAI_1 can be assumed to be Gaussian distributed. When there are only a small number of users or, where the power levels of the interfering users are significantly different, the central limit theorem will not be applicable, therefore, Eq.(4.5) will not be valid [35].

4.2.2 MMSE Detector

MMSE detector applies a linear transform $\mathbf{L}_{\text{MMSE}} = \left[\mathbf{R} + \sigma^2 \mathbf{A}^{-2}\right]^{-1}$ (as shown in Eq. (3.4)) to the soft output to the MF detector to minimize the MSE between the actual data and the soft output of the MMSE detector.

The decision statistic of user 1 can be expressed as [6]:

$$\tilde{z}_1 = B_1\left(b_1 + \sum_{k=2}^{K} \beta_k b_k\right) + \tilde{w}_1 \tag{4.6}$$

with

$$\beta_k = \frac{B_k}{B_1},$$

$$B_k = A_k (\mathbf{LR})_{1k}{}^{*}$$

and $\tilde{w}_1 \sim \mathcal{N}(0, \frac{\sigma^2}{N}(\mathbf{LRL})_{11})$ ▪, where $\mathbf{L} \triangleq \mathbf{L}_{\text{MMSE}}$ for the sake of conciseness.

Here β_k quantifies the contribution of the k^{th} interferer to the decision statistic, relative to the contribution of the user of interest.

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*$\mathbf{M}$ is a matrix, then $\mathbf{M}_{ik}$ means the element of the i^{th} row, k^{th} column in the $\mathbf{M}$.

▪ $\mathcal{N}(0, \sigma^2)$ refers to Gaussian distribution with zero mean and variance equal to σ^2.

As in deriving the BER expression for MF, the MAI in MMSE detector is assumed as a Gaussian random variable. Then, the BER approximation for MMSE detector can be given by

$$\mathrm{BER}_{\mathrm{MMSE}} = Q\left(\sqrt{\frac{A_1^2}{\tilde{\sigma}^2 + \sum_{k=2}^{K} \theta_k^2}}\right) \tag{4.7}$$

with

$$\tilde{\sigma}^2 = \frac{\sigma^2 \left(\mathbf{LRL}\right)_{11}}{N\left(\mathbf{LR}\right)_{11}^2},$$

$$\theta_k^2 = \frac{\left(\mathbf{LR}\right)_{1k}^2}{\left(\mathbf{LR}\right)_{11}^2} A_k^2 .$$

Here $\sum_{k=2}^{K} \theta_k^2$ refers to the interference power.

This approximation is accurate and has been supported by several analytical results, such as [38]. Here, we discuss about two asymptotic cases $\sigma \to 0$ and $\sigma \to \infty$. In the first case, as $\sigma \to 0$ the MMSE detector approaches the decorrelator ($\mathbf{L} = \mathbf{R}^{-1}$), and thus β_k vanish. In the second case, as $\sigma \to \infty$, the background AWGN contribution at the decision metric dominates the MAI. In either case, the decision metric is asymptotically Gaussian.

4.2.3 CPIC Detector

The structure of the CPIC detector is shown in Figure 4.1, where the detector bank refers to a MF bank. First, the received signal $r(n)$ in Eq.(4.3) passes to each MF detector to get the initial data estimates $\mathbf{b}^{(0)} = \left[\hat{b}_1^{(0)},...,\hat{b}_K^{(0)}\right]^T$ (refer Eq. (4.4)), which can be referred as the initial stage of the CPIC. Based on the data estimates, the transmitted signals of all users are regenerated. Here it should be noted that although there is an "amplitude estimator" block in the figure, we assume a perfect knowledge of amplitude as stated in Section 4.1. Then, the partial summer sums up all but the one user's signal, which creates the interference estimate for that particular user ($\hat{I}_k^{(1)}(n)$, k=1,…,K) as shown below:

$$\hat{I}_k^{(1)}(n) = \sum_{i=1, i\neq k}^{K} \hat{s}_i^{(0)}(n) = \sum_{i=1, i\neq k}^{K} A_i \hat{b}_i^{(0)} g_i(n), \tag{4.8}$$

where $\hat{s}_i^{(0)}(n)$ is the regenerated signal of the interferer (i^{th} user) and $\hat{b}_i^{(0)}$ is the tentative data estimate in the initial stage. Then $\hat{I}_k^{(1)}(n)$ is subtracted from the received signal to form the interference-suppressed signal $(r_k^{(1)}(n),\ k=1,...,K)$ as

$$r_k^{(1)}(n) = r(n) - \hat{I}_k^{(1)}(n)\,. \tag{4.9}$$

All these signals pass on to the next MF detector bank to produce a better set of data estimates $\hat{\mathbf{b}}^{(1)}$ for all the users.

In the CPIC, the data estimates are generated by MFs. Therefore, an interfering signal which is detected by MF with the wrong sign will be cancelled incorrectly, and thus, it will have its amplitude doubled (power quadrupled). If the signal is detected correctly, it will be cancelled completely. For example, if signal from user k is detected by MF incorrectly, the interference power from user k after one-stage cancellation is quadrupled to $4A_k^2\rho_{1k}^2$. The probability of this situation is $\text{BER}_{\text{MF}k}$, where $\text{BER}_{\text{MF}k}$ is the

BER for user k using Eq. (4.5) by taking user k as the desired user. On the other hand, if signal from user k is detected correctly, the probability of which is $(1\text{-BER}_{\mathrm{MF}k})$, the interference power from user k is zero. Then the expectation of interference power from user k is $4\mathrm{BER}_{\mathrm{MF}k} \bullet A_k^2 \rho_{1k}^2 + (1\text{-BER}_{\mathrm{MF}k}) \bullet 0 = 4\mathrm{BER}_{\mathrm{MF}k} \bullet A_k^2 \rho_{1k}^2$. As a result, the expectation of interference power from all the interferers (k=2,…,K) is equal to $4\left(\sum_{k=2}^{K} \mathrm{BER}_{\mathrm{MF}k} A_k^2 \rho_{1k}^2\right)$. Assuming that the outputs of the MFs in the bank are independent and the interference after one stage of cancellation is Gaussian distributed, the BER of CPIC detector can be described as [35]:

$$\mathrm{BER}_{\mathrm{CPIC}} = Q\left(\sqrt{\frac{A_1^2}{\frac{\sigma^2}{N} + 4\left(\sum_{k=2}^{K} \mathrm{BER}_{\mathrm{MF}k} A_k^2 \rho_{1k}^2\right)}}\right), \tag{4.10}$$

Although the data estimates of the MFs are dependent, they are not strongly dependent. Hence, for sufficiently large K, it is reasonable to assume the Gaussian model for the residual interference. The accuracy of this model improves as K increases [33].

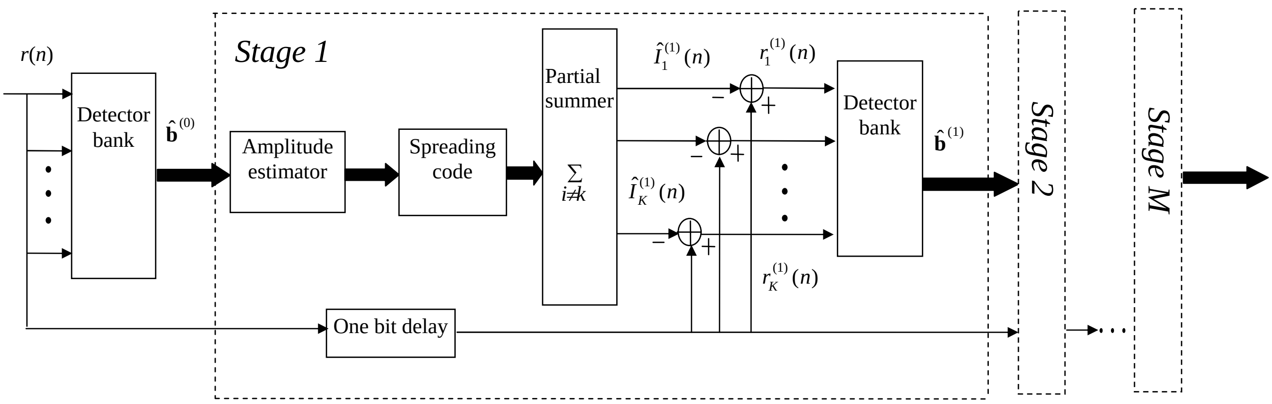

Figure 4.1. Structure of the PIC detector.

4.3 APIC Scheme

As discussed before, by improving the accuracy of the data estimates, the PIC detector can suppress the interference much more efficiently, *i.e.* more near-far resistant. Motivated by this, an adaptive PIC (APIC) scheme is proposed, which combines a simple blind adaptive MMSE (BAMMSE) detector with the PIC detector. In addition, the BAMMSE detector can suppress the inter-cell interference. As a result, the APIC can also suppress this interference, which cannot be suppressed by CPIC. In the following subsection, the structure of the proposed detector and its BER expression are presented. Performance of the detector in the multi-cell environment is also analyzed.

4.3.1 The Structure and Theoretical Analysis of the APIC Scheme

The structure of the APIC scheme is same as that in Figure 4.1. Here, the detector bank refers to BAMMSE detector bank (instead of the MF bank in CPIC), which contains K detectors for each user.

The structure of BAMMSE detector for a specific user, say user k, is shown in Figure 4.2. Here the adaptive filter is a TDL, and its detailed structure can be seen in Figure 3.3. The BAMMSE detector is the decision-directed version [1] of the adaptive MMSE detector proposed in [9,13]. In adaptive equalizer, the decision-directed operation is a scheme for continuous adjustment of the tap weights, in which, decisions on the information symbols are assumed to be correct and used in place of the accurate symbols to form the error [1]. Therefore, training sequences is not required in this scheme. Applying this idea in multiuser detection, BAMMSE detector is achieved and its cost function at the l^{th} bit is given by

$$E\left[\left|e_k(l)\right|^2\right] = E\left[\left|\hat{b}_k(l) - \mathbf{c}_k{}^T(l)\mathbf{r}(l)\right|^2\right] \tag{4.11}$$

where $\mathbf{c}_k(l) = \left[c_k^{(1)}(l), \ldots, c_k^{(N)}(l)\right]^T$ is the vector of N tap weights after the (l-1)$^{\text{th}}$ update and $\mathbf{r}(l)$ is vector of the received signal samples (sampled at chip rate) over the l^{th} bit duration, which is same as the vector $\mathbf{r}_k(l)$ in Eq. (3.6) with $\tau_k = 0$, k=1,…,K.

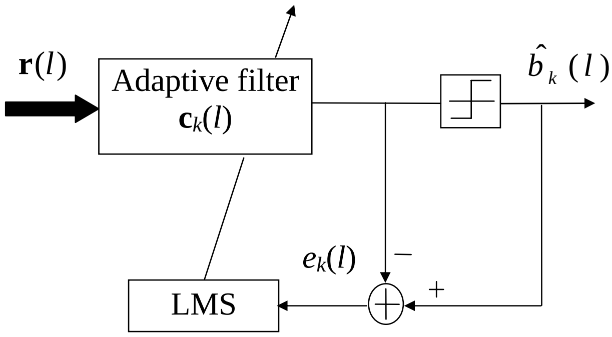

Figure 4.2. Structure of the BAMMSE detector for the k^{th} user.

LMS algorithm is used to search for the optimal weights for its low complexity (as discussed in Chapter 3, Subsection 3.2.3). The corresponding weights update is given by,

$$\mathbf{c}_k(l+1) = \mathbf{c}_k(l) + \mu \cdot e_k(l) \cdot \mathbf{r}(l), \tag{4.12}$$

where μ is convergence parameter (defined in Chapter 3). Since the spreading codes of the users concerned are available at the base station as mentioned in Chapter 1, the initial value of the weights for each user can be set to its corresponding spreading code.

As long as the detector is operating at low error rates, an occasional error will have only negligible effect on the convergence of the algorithm. Thus it has much improved performance over the MF, and will be demonstrated using numerical simulations in Section 4.4. In addition, using BAMMSE detector is consistent with trying to maintain simplicity, in which no extra information are needed beyond what is already provided for the MF.

In the APIC, the initial data estimates are generated by BAMMSE detectors. Then, after one stage cancellation, the remaining signals pass to another bank of BAMMSE detectors. Comparing with the CPIC, the only difference is that the APIC uses BAMMSE detectors for data estimation instead of MFs. Following the similar idea while deriving the BER expression for CPIC, an analytical expression of the APIC detector can be achieved. If signal of user k is incorrectly detected by BAMMSE, the interference power from user k after one-stage cancellation is $4\theta_k^2$, and θ_k^2 is defined in Eq. (4.7). The probability of this situation is $\mathrm{BER}_{\mathrm{MMSE}k}$, where $\mathrm{BER}_{\mathrm{MMSE}k}$ is the BER of user k using Eq. (4.7) by taking user k instead of user 1 as the desired user. If user k is detected correctly, the interference power from it is zero. As a result, the expectation of interference power from all the interferers is $4\left(\sum_{k=2}^{K}\mathrm{BER}_{\mathrm{MMSE}k}\theta_k^2\right)$. Assuming the BAMMSE detectors of the bank are independent and the interference after cancellation is Gaussian distributed, the BER for APIC is expressed as

$$\mathrm{BER}_{\mathrm{APIC}} = Q\left(\sqrt{\frac{A_1^2}{\tilde{\sigma}^2 + 4\left(\sum_{k=2}^{K}\mathrm{BER}_{\mathrm{MMSE}k}\theta_k^2\right)}}\right), \tag{4.13}$$

Similar to Eq. (4.10), the accuracy of Gaussian model for the residual interference improves as the number of users increases.

4.3.2 Performance Analysis in Multi-Cell Environment

All the analyses presented in the previous sections are with respect to single cell system, *i.e.*, only the MAI in the same cell as the desired user, known as intra-cell interference, is considered. In a cellular DS-CDMA system, a signal transmitted in one cell may cause interference in neighboring cells, known as inter-cell interference. This inter-cell interference is an intrinsic problem in the cellular DS-CDMA system. Therefore, if this interference is not considered in the multiuser detector design, the potential gain is significantly reduced. The performance in multi-cell environment is studied in this subsection.

Since MF and BAMMSE detectors need only the spreading code of the interested user, their performance analyses are same as that in the single cell situation. The difference between the two detectors is as follows. MF detects the desired user' signal as if it were the only one present, hence it can suppress neither intra-cell nor inter-cell interference; on the other hand, the adaptive nature of the BAMMSE detector allows it to learn the required information and adjust itself to suppress both intra-cell and inter-cell interferences.

In the PIC detectors, the interference estimates need the information of the corresponding users, as stated in Eq. (4.8). Since a base station is only equipped with the knowledge of those users in its own cell, interference cancellation can only cancel the intra-interference (related to the in-cell users). We assume that there are K_C users in the cell among all the K users. So the interference power contributed by the out-cell users (users K_C+1 to K) remains same even after interference cancellation. Therefore, after one-stage cancellation, the expectation of intra-cell interference power (from users k=2,…,K_C) are $4\left(\sum_{k=2}^{K_C}\mathrm{BER}_{\mathrm{MF}k}A_k^2\rho_{1k}^2\right)$, $4\left(\sum_{k=2}^{K_C}\mathrm{BER}_{\mathrm{MMSE}k}\theta_k^2\right)$ for CPIC and APIC, respectively, as stated in Subsections 4.2.3 and 4.3.1. The inter-cell interference power (from user k= K_C+1,…K) maintains the same as before the interference cancellation, *i.e.*, $\sum_{k=K_C+1}^{K}A_k^2\rho_{1k}^2$ $\sum_{k=K_C+1}^{K}\theta_k^2$ for CPIC and APIC, respectively, as stated in Subsections 4.2.1 and 4.2.2. Then, the BER expression for CPIC and APIC in multi-cell environment can be expressed as follows (in the theoretical calculation, ρ_{1k} and θ_k, k=1,…,K are assumed to be known):

$$\mathrm{BER}_{\mathrm{CPIC}}=Q\left(\sqrt{\frac{A_1^2}{\frac{\sigma^2}{N}+4\left(\sum_{k=2}^{K_C}\mathrm{BER}_{\mathrm{MF}k}A_k^2\rho_{1k}^2\right)+\sum_{k=K_C+1}^{K}A_k^2\rho_{1k}^2}}\right), \tag{4.14}$$

$$\mathrm{BER}_{\mathrm{APIC}}=Q\left(\sqrt{\frac{A_1^2}{\tilde{\sigma}^2+4\left(\sum_{k=2}^{K_C}\mathrm{BER}_{\mathrm{MMSE}k}\theta_k^2\right)+\sum_{k=K_C+1}^{K}\theta_k^2}}\right), \tag{4.15}$$

As mentioned before, the BAMMSE detector can suppress the inter-cell interference, therefore inter-cell interference power of APIC $\sum_{k=K_C+1}^{K}\theta_k^2$ is expected to be much smaller than that of CPIC, $\sum_{k=K_C+1}^{K}A_k^2\rho_{1k}^2$.

Now, we may argue that the improved performance of the proposed APIC scheme is the result of following facts. In the APIC scheme, BAMMSE detectors are used to generate the data estimates, which are much more accurate than the data estimates generated by the MF detectors. Better tentative data estimates allow more effective interference cancellation. This means that we exploit the accuracy of the BAMMSE detector and the interference suppression property of the PIC detector to achieve the improved near-far resistance capability. Moreover, the BAMMSE detector can suppress the interference from other cells that cannot be suppressed by CPIC. As a combined effect, the APIC can mitigate the inter-cell interference. Therefore, the overall MAI cancellation capability of the APIC scheme will be improved. In the following section, the performance of the APIC detector is examined through numerical simulations.

4.4 Simulation Results

This section deals with the simulation studies for the proposed APIC scheme. Its performance is compared with that of the MF, BAMMSE and CPIC detectors under various simulation conditions and the corresponding results are illustrated in Figures 4.3-4.5. All of the simulation results are verified with the theoretical results. The BER is used as the performance index for comparison purpose. In all of our simulations, spreading codes are chosen to be short Gold codes with the processing gain, N=31. The first user is assumed to be the user of interest. For CPIC and APIC detectors, one stage of cancellation is applied and the impact of additional stage on the performance will be studied in the next chapter.

4.4.1 Perfect Power Control Case

First, the perfect power control case is examined. This set of results show the BER curves as a function of SNR for desired user (user 1), $SNR = E_b / N_0$. BER estimation is done right from the beginning*, and each value is an average over 100 independent runs. Step size μ for all the adaptive algorithm, *i.e.* BAMMSE, APIC are set to 0.001. The number of users K is set to 30. The results are shown in Figure 4.3. Here, the theoretical BER curves of MF, BAMMSE, CPIC and APIC schemes are marked as lines and generated using Eqs.(4.5), (4.7), (4.10) and (4.13), respectively, with A_k^2 equal to one (perfect power control). It can be observed that the simulation results agree very well with the theoretical results.

For the perfect power control case, we find that all the multiuser detectors are better than the MF detector as expected. The CPIC scheme shows a little improved performance over the BAMMSE detector in this case. The APIC scheme shows the best performance even with equal powers, which does not take full advantage of the scheme. For example, to maintain BER at 0.001, APIC has almost 1.5dB gain in SNR over MF, 0.5dB over BAMMSE and 0.2 dB over CPIC.

* The convergence performance of BAMMSE detector is shown in Appendix A.

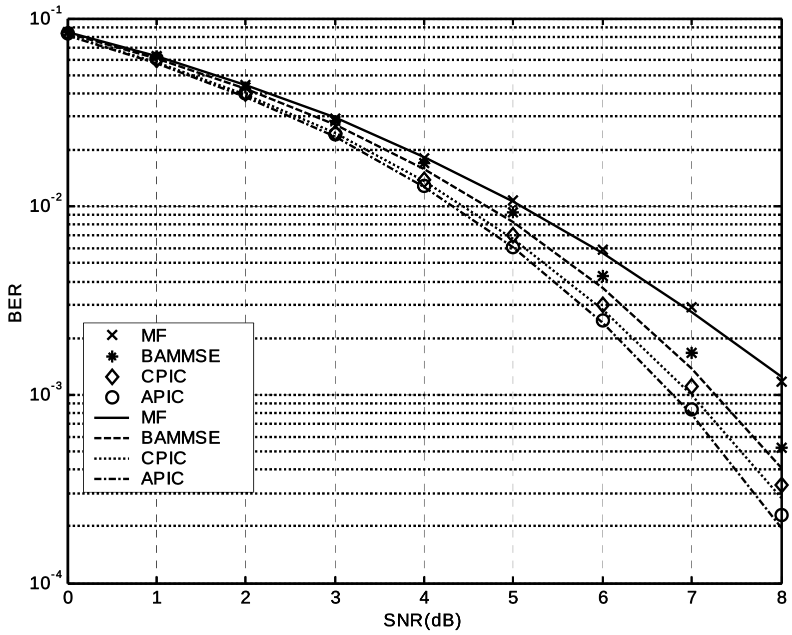

Figure 4.3. BER performance in perfect power control case with K=30.

4.4.2 Near-Far Case

In practice, the received powers of all users are not equal and DS-CDMA system is particularly limited by the near-far problem. To show the performance of the APIC in severe near-far situations, we divide the users into two groups with equal number of users: one group with powers four times that of the other group and the desired user is chosen to be one that belongs to the weak group. BER performances versus SNR are shown in Figure 4.4 with a high system load (K=30). Step size μ for all the adaptive algorithm, *i.e.* BAMMSE, APIC are set to 0.001. The theoretical BER performance for the various schemes are marked as lines and generated using Eqs.(4.5), (4.7), (4.10) and (4.13), with $A_k^2=1$ when $k=1,\ldots, K/2$ and $A_k^2=4$ when $k=(K/2)+1,\ldots K$. The simulation results show excellent agreement with the theoretical performance.

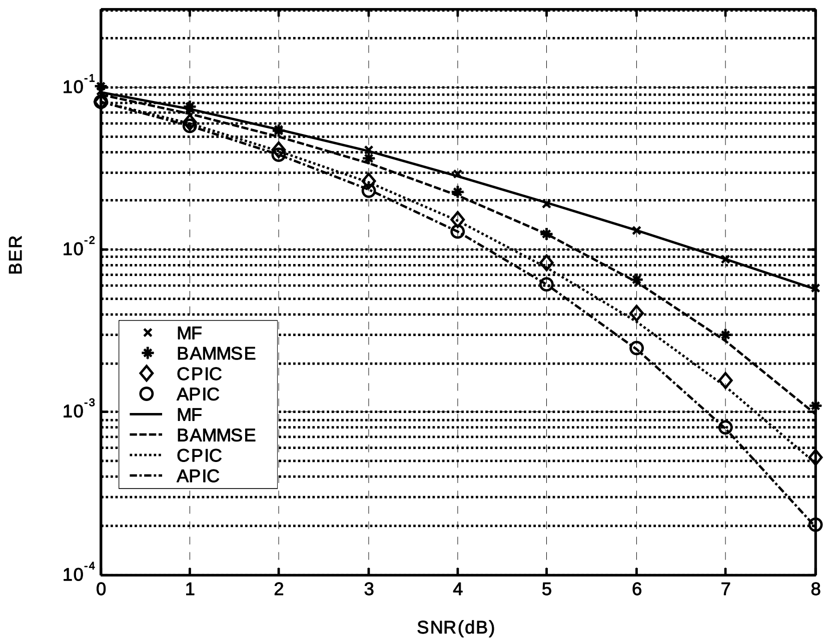

Figure 4.4. BER performance in near-far situation with K=30.

As illustrated in this figure, APIC shows improved performance over the other multiuser detectors. For a BER of 0.001, it can provide about 1 dB gain over BAMMSE and 0.5dB over CPIC. On comparing the results in Figures 4.3 and 4.4, it is observed that the unbalanced powers have almost no impact on the proposed APIC scheme, while it causes a drop in BER performance of MF, BAMMSE, CPIC, thus demonstrating APIC's near-far resistant property. This is due to the fact that in near-far condition, the MAI is much more dominant than that in perfect power control case. Moreover, the BAMMSE detector shows much better performance than the MF detector as shown in Figures 4.3 and 4.4. As a result, based on the data estimation of BAMMSE detector, the APIC suppresses the interference more effectively.

4.4.3 Multi-Cell Environment

As mentioned before, the potential of a multiuser scheme is significantly reduced if the inter-cell interference is disregarded. Therefore, the performances of the detectors in the presence of inter-cell interference are examined in this subsection. A quality caused as spillover ratio, which stands for the received total power ratio of the inter-cell interference over intra-cell interference, is introduced for this analysis.

Figure 4.5 shows the BER performance as a function of the number of users in the cell (K_C) for SNR=8dB. The spillover ratio is fixed at 0.5 and we assume that all the users have equal power. Step size μ for all the adaptive algorithm, *i.e.* BAMMSE, APIC are set to 0.001. Here, the theoretical BER curves are marked as lines and generated using Eqs. (4.5), (4.7), (4.14) and (4.15), respectively for MF, BAMMSE, CPIC and APIC schemes. It may be observed from Figure 4.5 that they agree with simulation results very well.

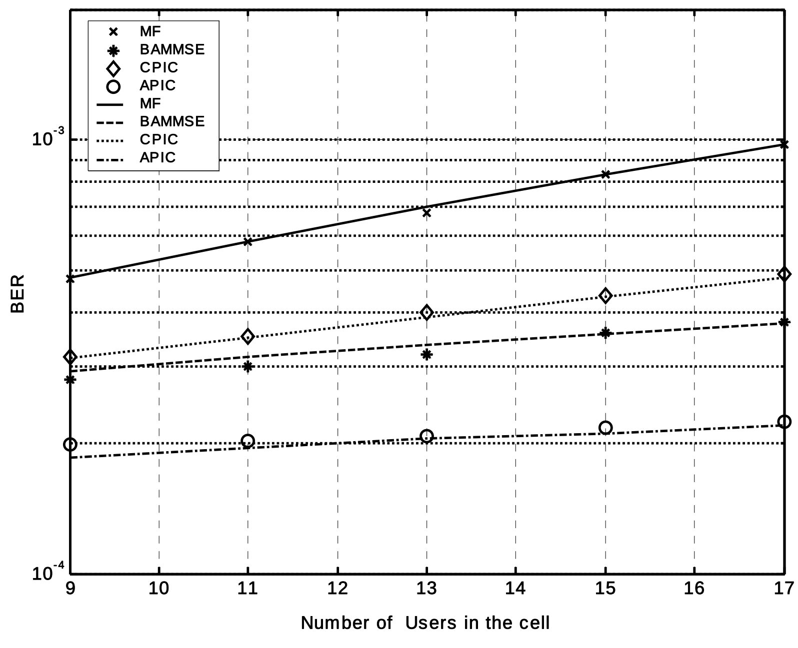

Figure 4.5. BER performance with spillover ratio=0.5 and SNR=8dB.

As is clear from this figure, MF shows the worst performance among all the schemes. Also, BAMMSE performs better than CPIC in the multi-cell environment, because BAMMSE is able to suppress the inter-cell interference, which cannot be suppressed by CPIC. Due to the combined effects as stated in Subsection 4.3.2, APIC shows much improved performance over CPIC in the presence of inter-cell interference. It can be seen from Figure 4.5 that to support 9 in-cell users, the BER performance of the proposed APIC scheme is 0.0002, while BER of CPIC is 0.00032. The difference becomes larger as the number of in-cell users increases.

4.5 Concluding Remarks

In this chapter, an adaptive PIC (APIC) scheme is proposed, which combines the attractive properties of the PIC and blind adaptive MMSE (BAMMSE) detectors. Through both numerical and analytical methods, it is shown that the proposed APIC detector has improved performance over CPIC and BAMMSE detectors.

PIC detector is designed to cancel MAI, therefore it has the potential to achieve further performance improvement for DS-CDMA systems. However, its performance is heavily dependent on the accuracy of the data estimation. In the proposed APIC scheme, the MF detectors (in the CPIC) are replaced by the BAMMSE detectors. In order to analyze the performance of the APIC detector, the comparisons with the other detectors, MF, BMMSE and PIC detectors, are provided in this chapter. The issues discussed here include near-far resistance and the capability to suppress the inter-cell interference. BER is used as the performance criterion. Through both analytical and numerical studies, the APIC detector is shown to have the best performance over the others. Especially, it is immune to the near-far problem and can suppress the inter-cell interference effectively.

CHAPTER 5

DECISION FEEDBACK PIC SCHEME BASED ON ADAPTIVE MMSE DETECTOR

In the APIC scheme presented in the previous chapter, BAMMSE detectors are used for data estimation instead of MF detectors (used in CPIC). Since the performance of BAMMSE detector is much better than the MF in the synchronous AWGN channel (as shown in last chapter), the APIC shows much improved performance over the CPIC. However, the performance of BAMMSE detector degrades when the channel is distorted, such as in asynchronous or fading channel. Therefore, the improvement of APIC over CPIC in these scenarios is not substantial. To overcome this problem, we propose an adaptive decision feedback PIC (ADFPIC) detector, which employs a decision feedback scheme to the APIC detector.

The remainder of the chapter is organized as follows. The system model is described in the next section. In Section 5.2, the structure of the proposed ADFPIC detector is described in detail along with a brief analysis. Section 5.3 presents the simulation results of the ADFPIC and APIC detectors in asynchronous channel and multipath fading channel. This chapter concludes with some final remarks in Section 5.4.

5.1 System Model

In this section, we will introduce the models for asynchronous channel and multipath fading channel.

5.1.1 Asynchronous Channel

Assuming there are K direct-sequence users in an asynchronous DS-CDMA system, the baseband received signal can be expressed as

$$\begin{aligned} r(t) &= \sum_{k=1}^{K} s_k(t-\tau_k) + w(t) \\ &= \sum_{k=1}^{K} A_k b_k(t-\tau_k) g_k(t-\tau_k) + w(t) \end{aligned} \tag{5.1}$$

where $s_k(t)$, A_k, $b_k(t)$, $g_k(t)$ are the transmitted signal, amplitude, transmitted data, and spreading code waveform, respectively, of user k. Further, τ_k is the time-delay of k^{th} user and is usually assumed to be a multiple of the chip duration T_c, and $w(t)$ is the channel noise modeled as AWGN.

Despreading the received signal by the MF, the output of the k^{th} user during a particular bit can be represented as

$$z_k = \frac{1}{T_b} \int_{\tau_k}^{T_b+\tau_k} r(t) g_k(t-\tau_k) dt \tag{5.2}$$

and the data estimate as $\hat{b}_k = \operatorname{sgn}(z_k)$.

The received signal $r(t)$ is passed through a chip matched filter and sampled at chip rate, then its discrete model can be represented by

$$r(n) = \sum_{k=1}^{K} A_k s_k(n - n_k) + w(n)\,, \tag{5.3}$$

where $n_k = \lfloor \tau_k / T_c \rfloor$.

In the CPIC detector, MFs are used for data estimation at each stage. At the m^{th} stage, an interference suppressed received signal for user k is obtained as,

$$r_k^{(m)}(n) = r(n) - \sum_{i=1, i\neq k}^{K} \hat{s}_i^{(m-1)}(n - n_k)\,, \tag{5.4}$$

where $\hat{s}_i^{(m-1)}(n)$ is the regenerated signal of the interferer (i^{th} user) denoted as

$$\hat{s}_i^{(m-1)}(n) = A_i g_i(n) \hat{b}_i^{(m-1)}\left(\lfloor n / N \rfloor\right), \tag{5.5}$$

where $\hat{b}_i^{(m-1)}$ is the data estimates of the i^{th} user derived from MF at the $(m\text{-}1)^{\text{th}}$ stage.

5.1.2 Multipath Fading Channel

Any system with mobile transmitters and/or receivers is subject to fading, which is due to the interference between two or more versions of the transmitted signals arriving at different angles with different delays. These multipath components cause amplitude, time and phase variations in the received signal.

The multipath fading channel is often assumed to be wide-sense stationary with uncorrelated scattering [1]. Based on this assumption, the channel model for the k^{th} user can be written as

$$h_k(\tau;t) = \sum_{p=1}^{P} \alpha_{kp}(t)\delta(\tau - \tau_{kp}) \tag{5.6}$$

where P is the number of paths of the channel, $\delta(.)$ is the unit impulse function, τ_{kp} is the propagation delay and is usually assumed to be a multiple of the chip duration T_c, and $\alpha_{kp}(t)$ represents the complex-valued time varying channel parameter taking into account the amplitude attenuation and phase shift. In Rayleigh fading channels, $\alpha_{kp}(t)$ is a complex Gaussian random variable with mean zero. Its amplitude has a Rayleigh distribution with a probability density function [6]

$$f_R(r) = \begin{cases} re^{-r^2/2} & r \geq 0 \\ 0 & r < 0. \end{cases} \tag{5.7}$$

Then, the received signal over the multipath fading channel can be written as

$$r(t) = \sum_{k=1}^{K} \sum_{p=1}^{P} \alpha_{kp}(t) s_k(t - \tau_{kp}) + w(t)\,. \tag{5.8}$$

Here, we assume that the transmitted signal undergoes slow fading, *i.e.*, $\alpha_{kp}(t)$ is constant for one bit duration.

In multipath fading channel, the RAKE receiver [39] can be used to combine the arriving time-delayed multipath components of the transmitted signal. Its structure for the k^{th} user is shown in Figure 5.1. The P "fingers" or branches of the RAKE receiver are to track the P multipath components of user k. The first part of the receiver is a bank of MFs, which is dedicated to the P multipaths for each user (user k). As a result, in a K user system, there are totally $K \times P$ MFs. As shown in Figure 5.1, the MF at each finger produces a decision statistic z_{kp} which reflects the strength and reliability of a given path component. In a particular bit duration, the output of p^{th} finger is

$$z_{kp} = \frac{1}{T_b} \int_{\tau_{kp}}^{T_b + \tau_{kp}} r(t) g_k (t - \tau_{kp}) dt \, ; \quad p=1,\ldots,P. \tag{5.9}$$

Then, based on the maximal ratio combining rule [1], the final decision statistic can be computed as,

$$z_k = \sum_{p=1}^{P} \alpha_{kp}^* z_{kp} \, , \tag{5.10}$$

where * denotes complex conjugation. The corresponding data estimate is given by $\hat{b}_k = \text{sgn}(\text{Re}\{z_k\})$.

The received signal $r(t)$ the received signal is passed through a chip matched filter and sampled at chip rate, then its discrete model can be written as:

$$r(n) = \sum_{k=1}^{K} \sum_{p=1}^{P} \alpha_{kp} s_k (n - n_{kp}) + w(n) \, , \tag{5.11}$$

where $n_{kp} = \lfloor \tau_{kp} / T_c \rfloor$.

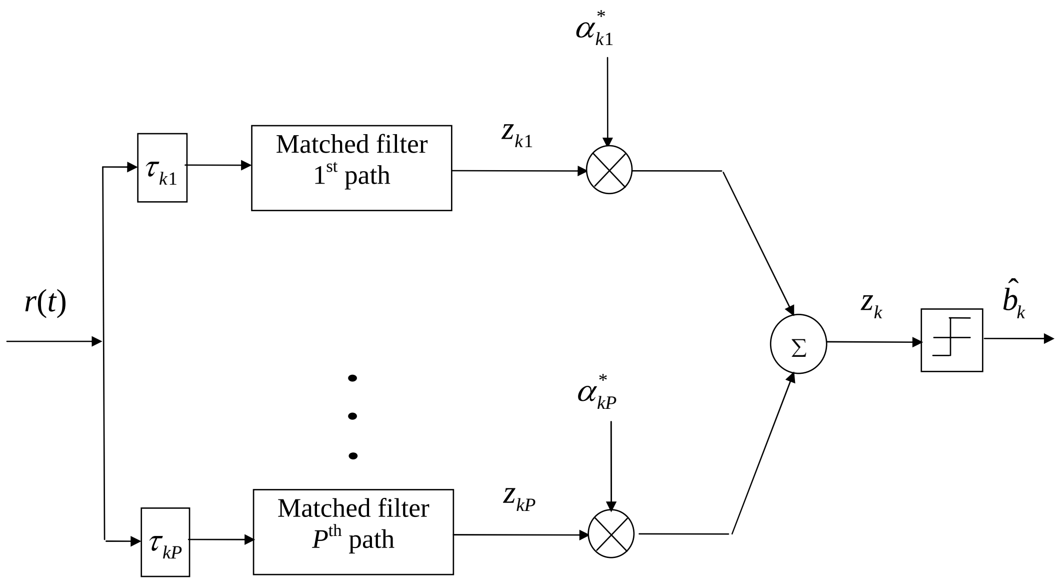

Figure 5.1. Structure of the RAKE receiver for the k^{th} user.

In multipath fading channel, the CPIC detector can use RAKE receiver at each stage for data estimation. The interference suppressed signal at the m^{th} stage for user k is

$$r_k^{(m)}(n) = r(n) - \sum_{i=1, i\neq k}^{K} \sum_{p=1}^{P} \alpha_{ip} \hat{s}_i^{(m-1)}(n - n_{kp}), \tag{5.12}$$

where

$$\hat{s}_i^{(m-1)}(n) = A_i g_i(n) \hat{b}_i^{(m-1)}\left(\lfloor n/N \rfloor\right) \tag{5.13}$$

and $\hat{b}_i^{(m-1)}$ is the data estimate of i^{th} user from RAKE receiver in the $(m\text{-}1)^{th}$ stage.

As stated in Chapter 4, in the following discussion, we assume a perfect knowledge of the parameters such as signal attenuation and delays at the detectors.

5.2 ADFPIC Scheme

In this section, the structure of the BAMMSE detector in asynchronous channel as well as multipath channel is described first. This is followed by a detailed description of the structure of the proposed ADFPIC scheme.

5.2.1 Modified Structure of BAMMSE Detector

The BAMMSE* detector in the APIC scheme is the decision-directed version of the adaptive MMSE detector. Its structure for user k in synchronous case is shown in Figure 4.2. It is the same for asynchronous case except that the input is changed to $\mathbf{r}_k(l)$ (instead of $\mathbf{r}(l)$). Here, $\mathbf{r}_k(l)$ means the vector of N received signal samples (sampled at chip interval $t = nT_c + \tau_k$) over l^{th} bit duration of k^{th} user. LMS algorithm is used for adapting the filter coefficients. The updating rule for the the k^{th} user can be written as,

$$\mathbf{c}_k(l+1) = \mathbf{c}_k(l) + \mu e_k(l)\mathbf{r}_k(l)\,, \tag{5.14}$$

where $\mathbf{c}_k(l) = \left[c_k^{(1)}(l),\ldots,c_k^{(N)}(l)\right]^T$ is the vector of N tap weights (coefficients) after the $(l\text{-}1)^{\text{th}}$ update, $e_k(l) = \hat{b}_k(l) - \mathbf{c}_k{}^T(l)\mathbf{r}_k(l)$ is the estimation error for the k^{th} user, and μ is the convergence parameter (defined earlier).

In multipath fading channel, we use precombining interference suppression type for BAMMSE scheme, *i.e.*, filtering for mitigating interference takes place prior to

* BAMMSE: "blind" means that this detector does not require the training sequences.

multipath combining. The performance of this type is generally inferior to postcombining interference suppression type in fixed multipath channel. However, the precombining one has less stringent tracking requirements than postcombining one and thus in principle, there are no constraints for their use in fading channels [40,41]. In the precombining interference suppression type, a blind adaptive filter is applied in every path for each user and thus totally $K \times P$ (the product of number of users with number of paths) filters are used. The structure of BAMMSE scheme over multipath fading channel for user k is shown in Figure 5.2. For the k^{th} user, the outputs from the blind adaptive filters in P paths are combined using the maximal ratio combining as shown in Eq. (5.10) to produce the data estimates $\hat{b}_k$. Then, the product of fading channel parameter α_{kp} and the estimated data $\hat{b}_k$ is used as the reference signal to update the weights of the adaptive filter in each path. The LMS updating rule for the weights at the p^{th} path of the k^{th} user can be written as

$$\begin{aligned} \mathbf{c}_{kp}(l+1) &= \mathbf{c}_{kp}(l) + \mu(\alpha_{kp}(l)\hat{b}_k(l) - z_{kp}(l))^* \mathbf{r}_{kp}(l) \\ &= \mathbf{c}_{kp}(l) + \mu e_{kp}^*(l)\mathbf{r}_{kp}(l), \end{aligned} \tag{5.15}$$

where $\mathbf{c}_{kp}(l) = \left[c_{kp}^{(1)}(l), \dots, c_{kp}^{(N)}(l)\right]^T$ is the vector of N tap weights after the $(l\text{-}1)^{\text{th}}$ update, $\mathbf{r}_{kp}(l)$ is vector of the received signal samples (sampled at instants $t = nT_c + \tau_{kp}$) over l^{th} bit duration, and $e_{kp}^*(l)$ is the conjugation of $e_{kp}(l) = \alpha_{kp}(l)\hat{b}_k(l) - z_{kp}(l)$.

As long as the detector is operating at low error rates, an occasional error will have only negligible effect on the convergence of the algorithm. However, in distorted channel, as the error rates increase, $\hat{b}_k$ is not so accurate, and therefore, BAMMSE detector will not be able to significantly outperform the MF or RAKE receivers. As a result, the APIC based on the BAMMSE detectors cannot show much performance improvement compared to the CPIC.

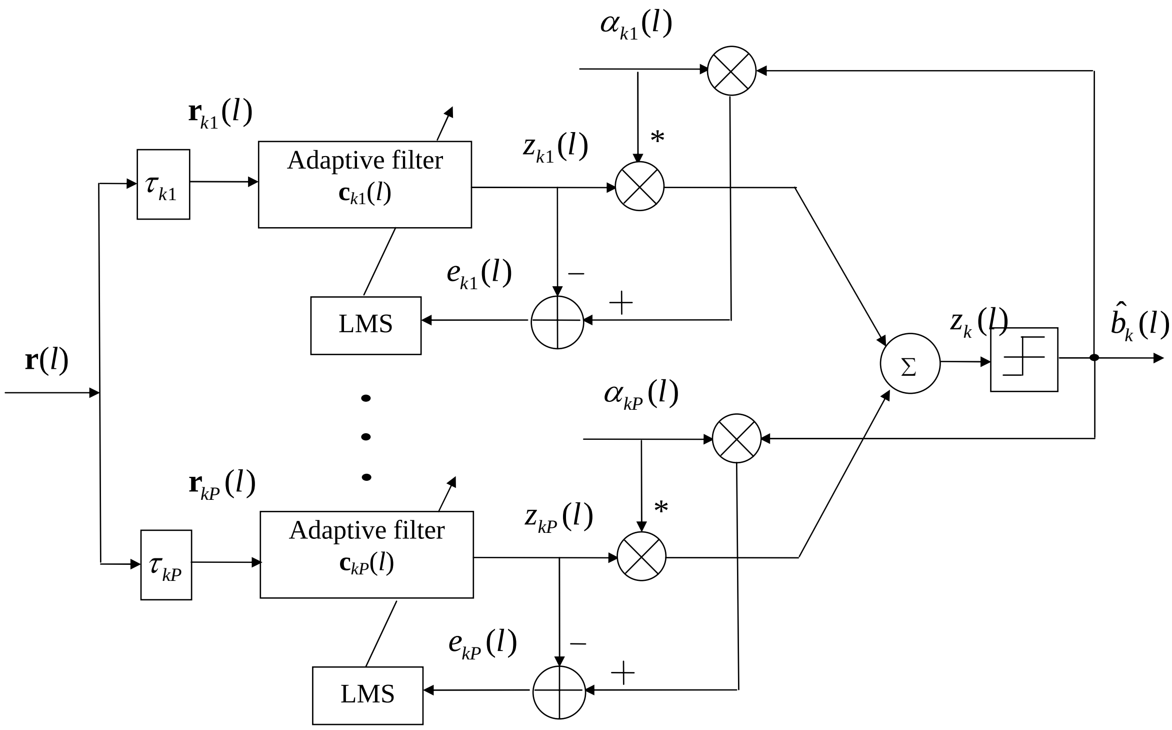

Figure 5.2. Structure of the BAMMSE detector for user k in multipath fading channel.

5.2.2 Structure of the ADFPIC Scheme

In the previous subsection, we discussed the problems faced by BAMMSE in distorted channels. In order to mitigate these problems and get further performance improvement, ADFPIC detector is proposed and its structure is shown below in Figure 5.3. Here it should be noted that although there is an “amplitude estimator” block in the figure, we assume a perfect knowledge of amplitude as stated in Section 5.1.

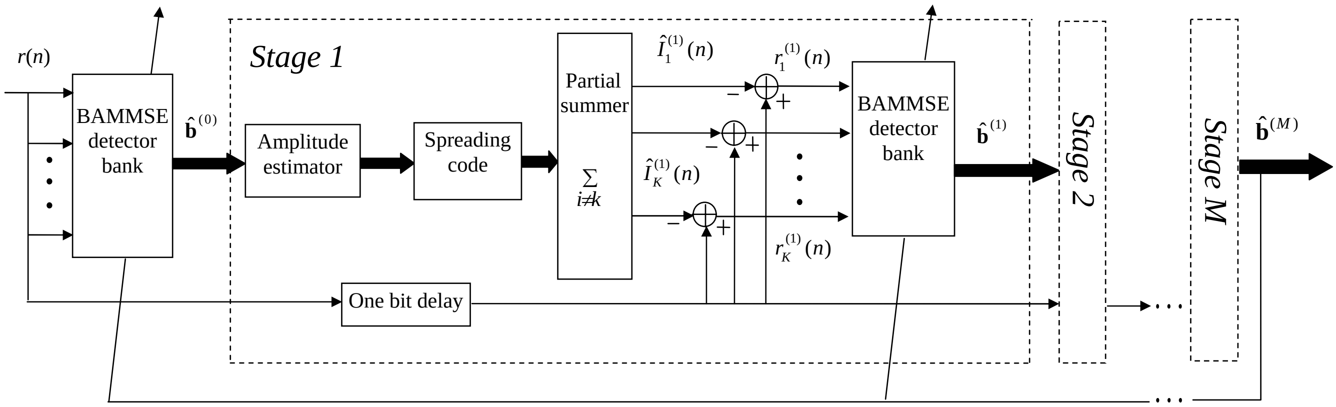

Figure 5.3. Structure of the proposed ADFPIC detector.

In this detector, we employ decision feedback scheme, *i.e.*, using the data estimates from the final stage M $\left(\hat{b}_k^{(M)}(k=1,...,K)\right)$ as the 'accurate' data to form the error to update the tap weights of BAMMSE detectors for the k^{th} user in the previous stages 0, 1,…, M-1. After M-stage cancellation, $\hat{b}_k^{(M)}$ is more accurate than the data estimates in the previous stages $\hat{b}_k^{(m)}(m=0,...,M-1)$, and thus the BAMMSE detector will have better performance. As a result, ADFPIC can achieve more performance improvement compared to APIC. The APIC and ADFPIC can be easily used in asynchronous channel as well as multipath fading channel conditions. The interference cancellation is same as that in CPIC shown in Eqs. (5.4) and (5.12) except that the data estimates in APIC and ADFPIC are derived from BAMMSE detectors.

5.3 Simulation Results

In this section, we present the findings of our simulation studies to evaluate the proposed ADFPIC scheme and compare it with the MF (or RAKE receiver in multipath fading channel), BAMMSE, CPIC and APIC schemes. BER is used as the performance criterion and short Gold code as the spreading code with N=31. The first user (k=1) is assumed to be the user of interest.

5.3.1 Asynchronous Channel

In the simulation studies of asynchronous channel, we assume that the delay of the interested user is 0 (τ_1=0). The delays of the other users are multiples of chip duration T_c, and are assumed to be available at the detectors.

We begin with the perfect power control case. Figures 5.4 and 5.5 show the BER curves as a function of SNR for desired user (user 1) with K=30, $SNR = E_b / N_0$. BER estimation is done right from the beginning. Step size μ for BAMMSE and APIC are set to 0.0001 and 0.001 for ADFPIC. The number of cancellation stages (M) for CPIC, APIC and ADFPIC are one in Figure 5.4, and two in Figure 5.5.

As shown in Figure 5.4, BAMMSE detector has a relatively slight improved performance over MF. Consequently, APIC does not show much improvement compared to CPIC. On the other hand, the proposed ADFPIC significantly outperforms the other multiuser schemes. For example, to maintain a BER of 0.02, ADFPIC can provide almost 2dB SNR gain over CPIC, while for APIC, the gain is about 1dB over CPIC. By increasing the number of stages to two as shown in Figure 5.5, the performances of CPIC, APIC and ADFPIC are all improved, especially the ADFPIC scheme, which has achieved about 1dB SNR gain given BER=0.02.

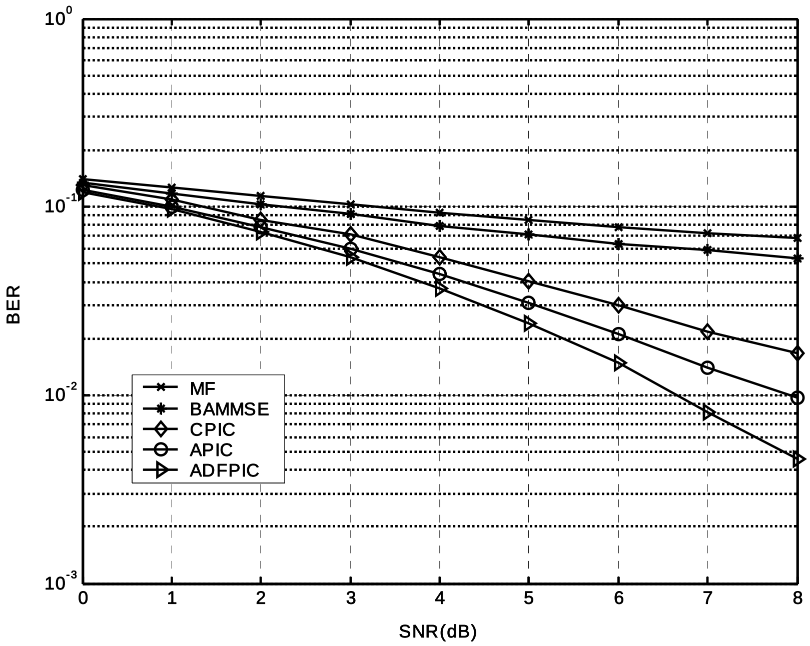

Figure 5.4. BER performance in asynchronous perfect power control situation with K=30 and M=1.

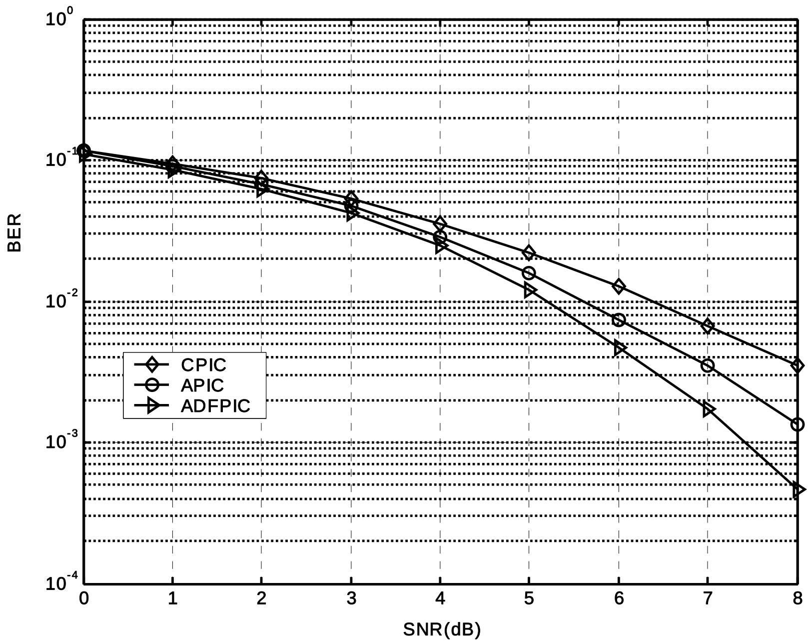

Figure 5.5. BER performance in asynchronous perfect power control situation with K=30 and M=2.

Figures 5.6 and 5.7 are obtained under the same conditions as those for Figures 5.4 and 5.5, respectively, except that the power control is now imperfect. Severe near-far condition is assumed, where the desired user's power is held constant at unity, and the near-far ratio (NFR) between all the interferers and the desired user is fixed at four ($\mathrm{NFR}_k = A_k^2 / A_1^2 = 4, \quad k = 2, \ldots, K.$).

Comparing these four figures, two observations can be made. The first one is that in the near-far cases (Figures 5.6 and 5.7), the proposed detectors (APIC and ADFPIC), especially ADFPIC, show much more improvement over the other detectors than that in the perfect power control cases (Figures 5.4 and 5.5). The other observation is that with an additional stage, substantial increase in performance of the proposed schemes (and CPIC) can be achieved in both cases; the increase is much more obvious in severe near-far condition compared to that in perfect power control case. This may be due to the following facts. The PIC is eminently suitable for the severe near-far situation (Figures 5.6 and 5.7), *i.e.*, demodulating the weak signal in the presence of the strong interference. The estimate for the strong interferer is generally good, and this results in beneficial cancellation of the strong interferer. In severe near-far case, strong interferers are dominant in numbers, *i.e.*, most of the data estimates are good at the initial stage. Thus after one stage cancellation, the data estimates for strong interferers are more accurate (the estimate for the weak user is also improved). Consequently, when the strong users are cancelled from the weak user's signal in the second stage cancellation, it is done much more accurately, resulting in much better performance of the weak user (user of interest). In addition, based on BAMMSE detectors and decision feedback scheme, ADFPIC shows strong ability in interference cancellation.

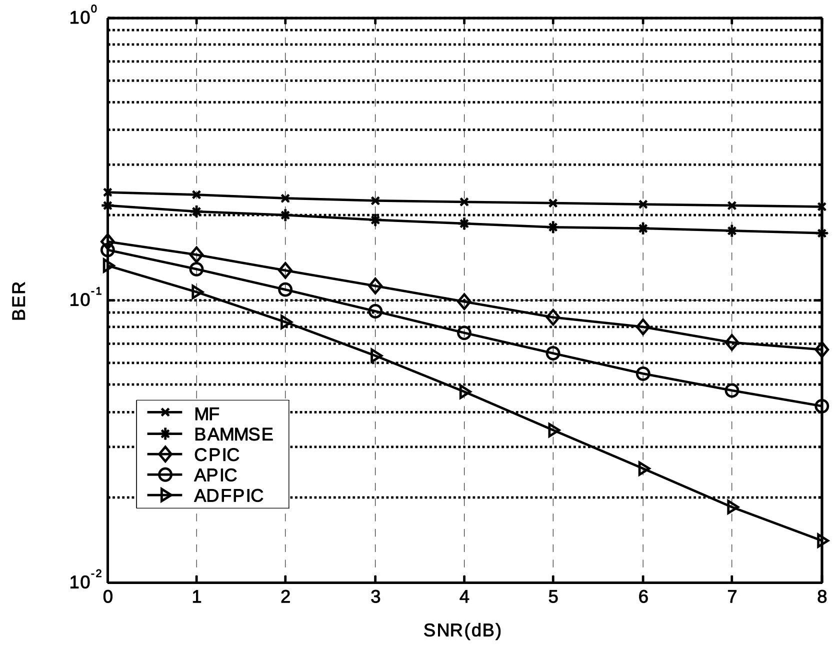

Figure 5.6. BER performance in asynchronous near-far situation with K=30 and M=1.

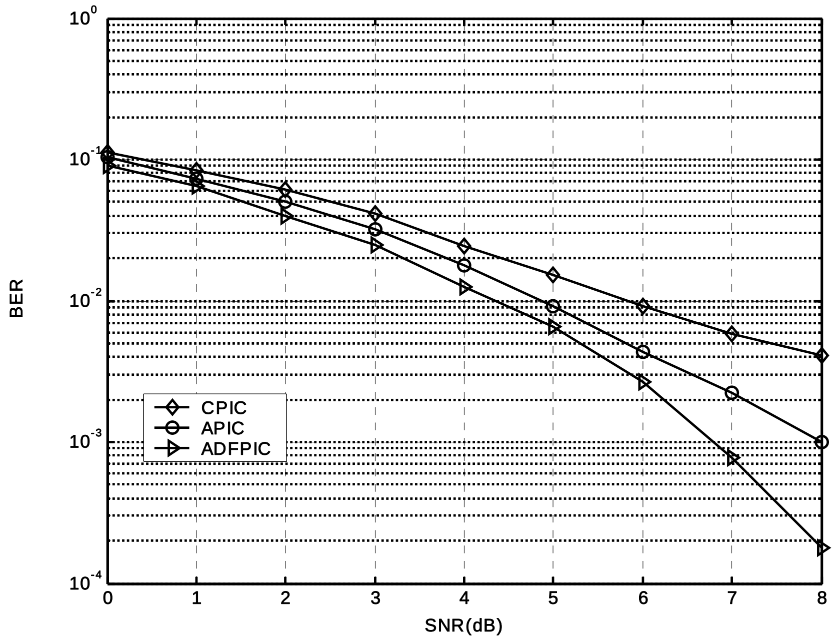

Figure 5.7. BER performance in asynchronous near-far situation with K=30 and M=2.

5.3.2 Rayleigh Fading Channel

The performance of various schemes in a two-path (P=2) Rayleigh fading channel is illustrated in Figures 5.8 and 5.9 for 15 users with perfect power control. Step size μ for all adaptive algorithm, *i.e.*, BAMMSE, APIC and ADFPIC are set to 0.0001.The number of cancellation stages (M) for CPIC, APIC, ADFPIC are set to one in Figure 5.8, and two in Figure 5.9. In the simulation, the propagation delay τ_{kp} is multiple of the chip duration T_c and is assumed to be available at the detectors. The channel gain is normalized for each user $E\left[\sum_{p=1}^{P}\left|\alpha_{kp}(t)\right|^2\right]=1$.

As shown in Figure 5.8, the ADFPIC detector outperforms the other schemes. For example, to obtain a given BER, say, 0.0006, ADFPIC and APIC provide 5dB and 3dB SNR gains, respectively over CPIC. With an additional cancellation stage (Figure 5.9), the performances of all the detectors are improved and ADFPIC still shows its superiority. For a BER of 0.0006, ADFPIC achieves almost 1.5dB gain over CPIC, while APIC has only a little improved performance over CPIC.

The improved performance of ADFPIC can be explained as follows. In the multipath fading channel, the performance of BAMMSE degrades. As clear from Figure 5.8, although BAMMSE detector outperforms MF, both performances are very poor. Moreover, their performances flatten out as SNR increases. This is due to the fact that MF cannot cancel the MAI and BAMMSE is also vulnerable to MAI in multipath fading channel. When SNR is high, MAI is dominant in the noise. As a result, they cannot achieve much performance improvement as SNR increases. Depending on the data estimates from BAMMSE, the performance of APIC detector also degrades. On the other hand, in ADFPIC, BAMMSE detector can work better through the feedback for more accurate data estimates. Consequently, based on the BAMMSE detectors, the ADFPIC can remove the MAI more efficiently compared to the other schemes.

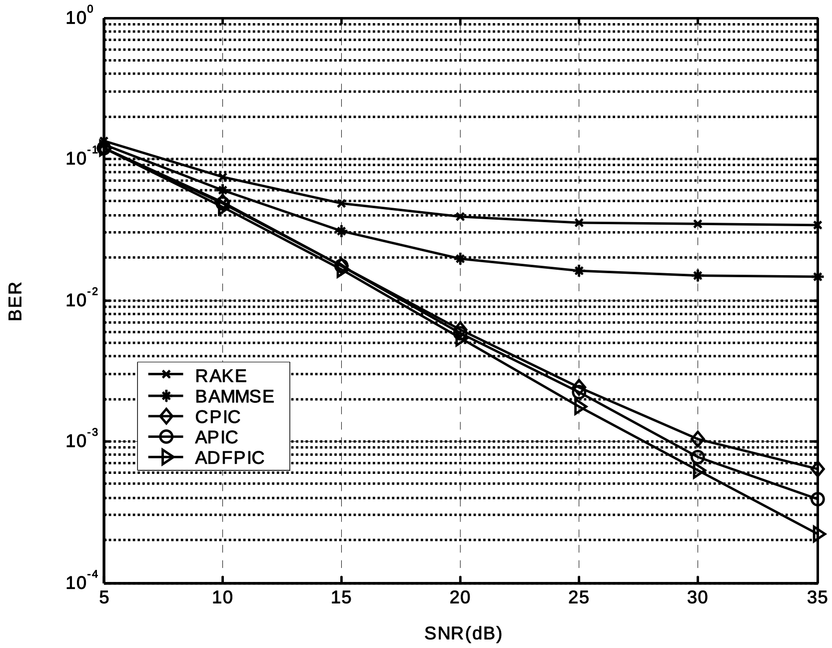

Figure 5.8. BER performance in two-path Rayleigh fading channel with *K*=15 and *M*=1.

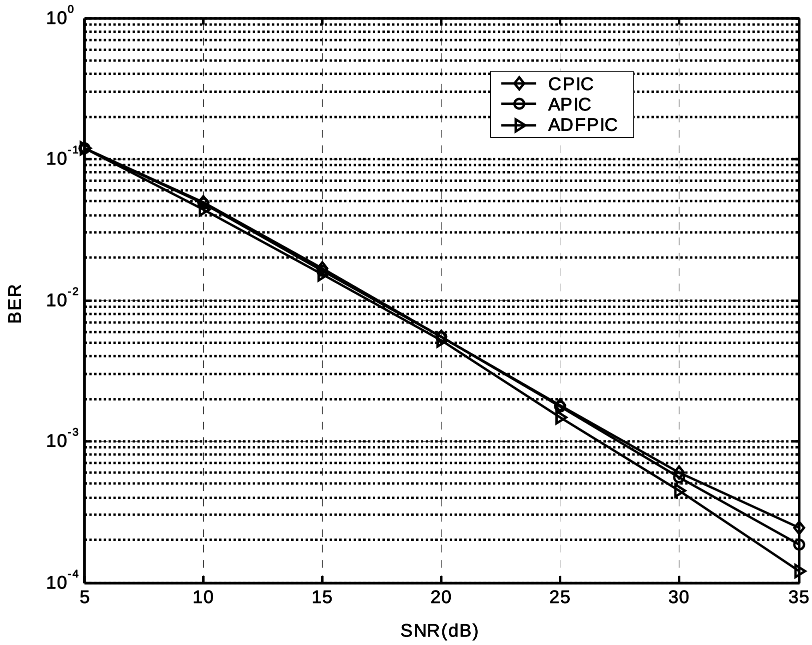

Figure 5.9. BER performance in two-path Rayleigh fading channel with *K*=15 and *M*=2.

5.4 Concluding Remarks

In this chapter, an adaptive decision feedback PIC (ADFPIC) detector is proposed, which applies a decision feedback scheme to APIC detector. Through the simulations in asynchronous channel as well as multipath fading channel, it is shown that the proposed scheme (ADFPIC) has improved performance over the APIC scheme.

The APIC scheme uses BAMMSE detectors for data estimation, which can achieve much better performance than CPIC as proved in the previous chapter. However, the BAMMSE performance degrades in distorted channel scenarios. Therefore, we propose an ADFPIC detector. In this detector, a decision feedback scheme is applied, where the data estimates in the final stage are used to update the BAMMSE detectors in the previous stages. Using this scheme, we can get more accurate tentative data estimates, and then the interference estimates will be more accurate, which result in effective MAI cancellation. The simulation results show that the proposed ADFPIC scheme outperforms other schemes under the various channel conditions.

CHAPTER 6

CONCLUSIONS AND FUTURE WORK

In this final chapter, we present conclusions based on the whole thesis and make recommendations for future research.

6.1 Conclusions and Contributions

In this thesis, we have proposed two PIC detectors based on the simple blind adaptive MMSE detectors:

- Adaptive PIC (APIC) detector, where blind adaptive MMSE (BAMMSE) detectors are used for data estimation in each stage instead of MFs (used in the CPIC detector).
- Adaptive decision feedback PIC (ADFPIC) detector, an improvement to APIC, where a decision feedback scheme is applied. Here, the data estimates in the final stage are used to update the BAMMSE detectors in the previous stages.

The properties of the PIC and adaptive MMSE detectors have motivated the development of an APIC scheme. PIC is designed to cancel the interference estimate, therefore, it has the potential for further performance improvement which is dependent on the accuracy of the data estimation. As the estimates from the previous stages improve, the performance of the multistage PIC is improved as a result. In the CPIC detector, the data estimates in each stage are derived from the MFs, which suffer from near-far situation, thus limiting the performance of PIC. One of the direct ways to overcome this problem is to use some other methods to replace MF. The BAMMSE detector is presented accordingly, which is shown to have improved performance than MF while retaining simplicity. As a result, in the APIC scheme, we exploited the interference cancellation property of PIC detector and the data estimation accuracy of the BAMMSE detector. Another advantage for this combination is that the adaptive nature of the BAMMSE detector allows it to adjust itself to suppress inter-cell interference, which cannot be suppressed by CPIC. Therefore, as a combined effect, APIC can suppress the inter-cell interference. Through both analytical and numerical simulation studies in synchronous AWGN channel, the APIC is shown to outperform the CPIC and BAMMSE detectors.

In distorted channel, as the error rates increase, the performance of BAMMSE detector degrades. To mitigate this problem and achieve further performance improvement, the ADFPIC detector is proposed. Through the decision feedback scheme, where the data estimates in the final stage are used to update the BAMMSE detectors in the previous stages, BAMMSE detector can work better. Thus, based on the BAMMSE detectors, the ADFPIC can suppress the MAI effectively. The simulation studies in the asynchronous channel as well as multipath fading channel have shown that the ADFPIC detector outperforms the APIC.

6.2 Future Work

We suggest the following topics for further research:

- Practical considerations of the schemes

  In a realistic system, it is difficult to attain perfect knowledge of channel parameters. Hence, it is needed to incorporate practical considerations in our proposed schemes in the future work. These include study of the effect of timing errors, imperfect phase and amplitude estimations etc.

- The Kalman filtering algorithm

  The Kalman filter is very powerful in several aspects: it supports estimations of past, present, and even future states, and it can do so even when the precise nature of the modeled system is unknown. Considering these attractive properties of Kalman filtering algorithm, it is interesting to use this algorithm in our scheme in future study.

- Chaotic spreading sequences.

  As mentioned in Chapter 2, the properties of the spreading codes play an important role in the DS-CDMA systems. Recently, a great research effort has been devoted towards the possibility of exploiting chaotic spreading sequences instead of pseudorandom noise (PN) sequences in the DS-CDMA systems [42]. The PN sequences are periodic and limited in numbers, while the noise-like feature of the chaotic sequence is more desirable in communication systems.

Therefore, it could be a good aspect to continue the work of our schemes using chaotic spreading codes.

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APPENDIX A

CONVERGENCE PERFORMANCE OF BLIND ADATPIVE MMSE DETECTOR

In order to examine the convergence performance of the BAMMSE detector, the simulations are done and the results are shown in Figures A.1 and A.2.

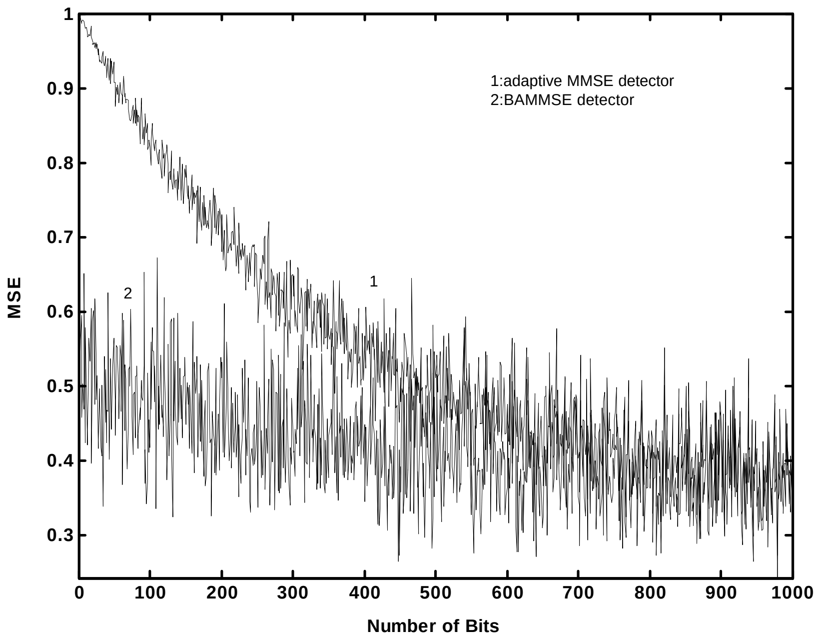

Figure A.1. Convergence curves of BAMMSE and adaptive MMSE detectors in perfect power control case with K=30, SNR=0dB, $m = 0.001$.

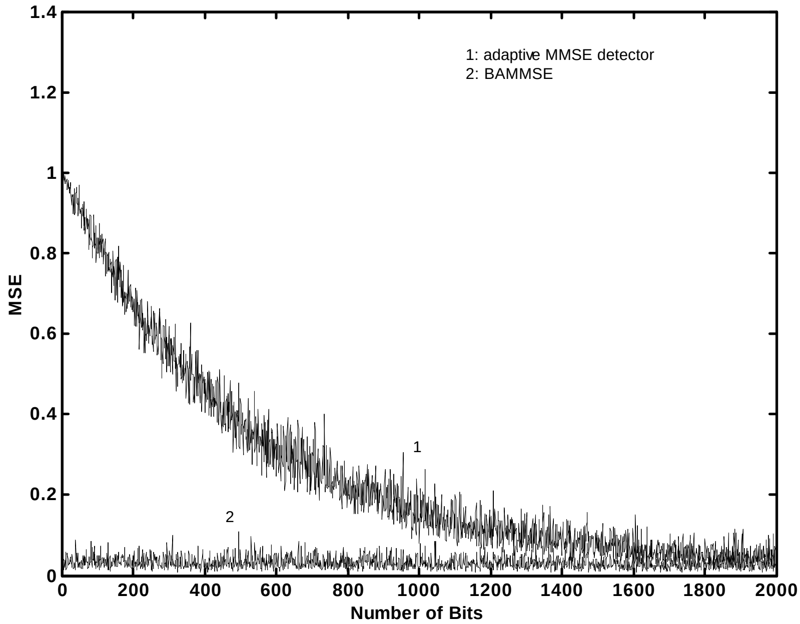

Figure A.2. Convergence curves of BAMMSE and adaptive MMSE detectors in perfect power control case with K=30, SNR=20dB, $m = 0.001$.

Figure A.1 shows the convergence performance, mean-square error (MSE) of the BAMMSE detector (discussed in Subsection 4.3.1), and the adaptive MMSE detector analyzed in [9,13], which is used as a reference of the steady state. The simulation results are obtained in a system with number of users K=30 in perfect power control case, and SNR=0dB. Figure A.2 is obtained under the same parameter settings as in Figure A.1, except the SNR which is set to 20dB now. As can be seen from the figures, the proposed BAMMSE detector converges very fast (in both low and high SNR cases) compared to the adaptive MMSE detector. In Figure A.1, the BAMMSE detector is close to the steady state at the beginning and achieves the steady state at about 300 bits. In Figure A.2, it achieves the steady state almost right from the beginning.

RESEARCH PAPERS ORIGINATED FROM THIS WORK

1. Du Lin and S. Puthusserypady, “A Novel Multiuser Detection Scheme Combining Adaptive MMSE Receiver and Parallel Interference Canceller for Near-Far Resistance,” *Proceedings of the 4th IEEE conference on Mobile and Wireless Communications Networks (MWCN)*, Sep. 2002, Stockholm, Sweden, pp. 191-121.
2. Du Lin and S. Puthusserypady, “Parallel Interference Cancellation Scheme Based on Adaptive MMSE Detector for DS-CDMA Systems,” *14th IEEE International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC)*, Sep. 2003, Beijing, China, pp. 1541-1545.
3. Du Lin and S. Puthusserypady, “An Adaptive Decision Feedback PIC for Asynchronous DS-CDMA System,” *IEEE Military Communications Conference (MILCOM)*, Oct. 2003, Boston, USA.
4. Du Lin and S. Puthusserypady, “Parallel Interference Cancellation Based on Adaptive MMSE Detection for DS-CDMA Systems,” Communicated to *IEEE Trans. On Wireless Commun.*
5. Du Lin and S. Puthusserypady, “An Adaptive PIC using Decision Feedback Scheme for DS-CDMA Systems in Fading Channels,” Communicated to *EURASIP J. on Wireless Commun. and Networking.*