AN ABSTRACT OF THE THESIS OF

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Sayfe Kiaei

Interference from other adjacent users in wireless applications is a major problem in direct-sequence code-division multiple-access (DS-CDMA). This is also known as the near-far problem where a strong signal from one user interferes with other users. The current approach to deal with the near-far problem in DS-CDMA systems is to use strict transmitter power control. An alternative approach is to use near-far resistant receivers. The practical near-far resistance receiver structure is the adaptive decorrelating detectors since it avoids complex matrix inversion.

The existing CDMA standard known as IS-95 uses a long signature code sequence. However for simplicity, the adaptive multi-user receiver uses short signature code sequence. The problem is that adaptive receivers lose near-far resistance as the number of users increases in the system. This thesis describes a novel method of multi-stage decision feedback cancellation (DFC) scheme immune from the near-far problem. The performance of the new DFC structure is constructed using three different adaptive algorithms: the least mean squared (LMS), the recursive least squared (RLS) and the linearly constraint constant modulus (LCCM) adaptive algorithms. It is found that LMS adaptive algorithm provides the best result considering its simple hardware complexity. It is also found that the LMS adaptive receiver along with the DFC structure provides a

better bit synchronization capability to the over all system. Since the receiver is near-far resistant, the LMS adaptive receiver along with the decision feedback cancellation structure also performs better in the presence of Rayleigh fading.

Interference Cancellation for Shot-Code DS-CDMA in the Presence of Channel Fading

by

Amit K. Dutta

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TABLE OF CONTENTS

TABLE OF CONTENTS (Continued)

LIST OF FIGURES

LIST OF FIGURES (Continued)

LIST OF FIGURES (Continued)

LIST OF FIGURES (Continued)

Figure | Page

LIST OF TABLES

Interference Cancellation for Short Code DS-CDMA in the Presence of Channel Fading

Chapter 1. Introduction

In wireless communications, multiple signals are transmitted over the channel by modulating each message as shown in Figure 1.1. Methods for transmitting several users on the same channel are known as multiplexing. There exist three known methods: frequency division multiple access (FDMA), time division multiple access (TDMA) and Code division multiple access (CDMA). In FDMA, each user occupies a specific portion of the allocated spectrum. In TDMA, each user transmits the signal at a known specific time. In CDMA, all users' messages are transmitted at all time and share the same spectrum, but are separated by a set of orthogonal codes. The main emphasis of this thesis is to examine interference of multi-user sharing the same spectrum in CDMA system.

Code Division Multiple Access (CDMA) uses code sequence with values +1 or -1 (each +/-1 is known as a chip) to multiplex several users on the same channel. The chip rate is much higher than the digital data rate, as shown Figure 1.2. The chip sequence for each user is generated from a pseudo-random number (PN) generator (normally a set of shift registers) so that it bears random characteristics. Without the knowledge of the chip sequence, the signal appears as a digital noise. The same principle of correlation is used in demodulating the signal to get the desired user's message.

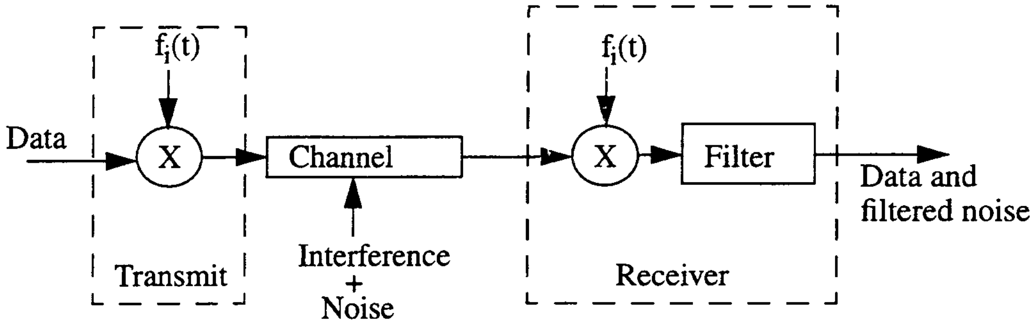


Figure 1.1 The single channel communication

CDMA has become a major contender for future cellular communications systems. Interim Standard IS-95 proposed by Qualcomm is the main standard for CDMA systems [56]. CDMA allows digital messages from separate users to be transmitted over the same frequency band by assigning to each user a unique chip sequence. For a receiver in the same frequency band, signals from other users appears as noise and therefore are rejected during demodulation. In IS-95, the standard defines signal modulation specifications for both the down link (also known as the forward link), - defined from the base station to the mobile station - and the reverse link or up-link, - defined from the mobile station to the base station. The modulator and demodulator for IS-95 are thoroughly discussed in IS-95 [56].

The major obstacles with CDMA system are synchronization, the Near-Far problem and the interference cancellation. In IS-95, decoding the down link signal at the mobile station is a simpler task than decoding the uplink at the base station. This result is due to synchronization. Since the signals transmitted from the base station are in phase with each other, a simple correlator at the receiver will eliminate most interference. This transmission from base station to the mobile unit user is known as DS-

CDMA synchronous transmission. However, the signals received at the base station are not synchronized and are received with arbitrary phase shift (different time delays). This transmission from mobile unit to base station is known as DS-CDMA asynchronous transmission. Since the coded received signals are not synchronized, orthogonality of the signals from different users is no longer guaranteed, making decoding more difficult.

The Near-Far problem is prominent only in the CDMA uplink, during transmission from mobile units to the base-station. The Near-Far problem occurs when a transmitter near the base-station produces a very strong signal causing interference in weaker signals to be received by the same base station. As explained earlier, during uplink transmission, the chip sequences are non-orthogonal as they are received asynchronously, which creates strong interference in conventional matched filter demodulation. In IS-95 standard, long code sequences are used and hence it is not possible to cancel the multi-user access interference term using a matched filter. Therefore, constant power control over all users are required. The power control enables all users' received power at the base station to be almost equal to reduce the near-far problem.

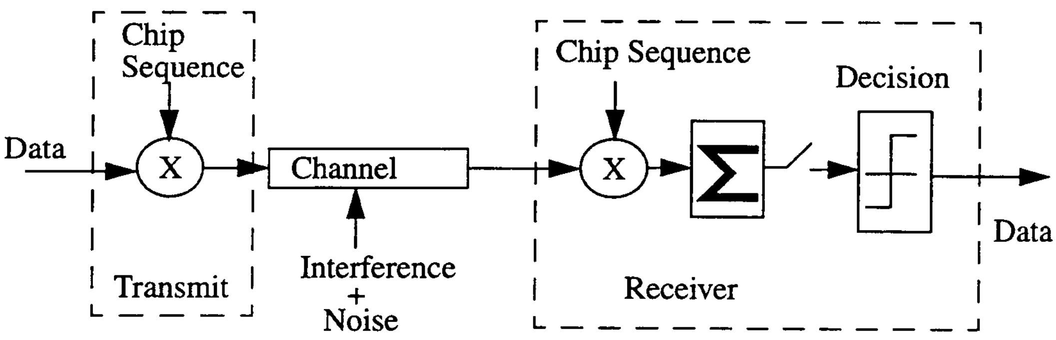


Figure 1.2 CDMA communications system at base band

Interference caused by other users with the desired signal due to non-orthogonality of codes is the third challenge. This problem is only prominent in uplink, where detection is difficult due to unknown nature of the delay associated with received signals from all users. This delay destroys the orthogonal property of the codes used for different users. In matched filter detection, interference due to other users becomes prominent. In the presence of large users, this interference makes correct detection of the desired signal virtually impossible.

Recently, work has been done to cancel the multiuser access interference term using short code (chip) sequences, thereby reducing the burden on power control. The classical paper by S. Verdu [8], followed by papers by R. Lupas [9][10][16], M.K. Varanasi, B. Azang [13][26][27] discuss this approach. The most recent work emphasizes on use of adaptive system to avoid use of matrix inversion simplifying the receiver. It has been noticed that if there are large number of users, the adaptive decorrelating detectors lose the near-far resistance, thus requiring stringent power control. This thesis proposes a new receiver that increases the near-far resistance of the adaptive decorrelating detector during the uplink to the base station. In addition to that, this thesis explores complexity and accuracy of three different, standard adaptive implementation, least mean square (LMS), recursive least square (RLS) and linearly constrained constant modulus (LCCM) adaptive algorithms to enhance the performance of the demodulator, as well as, synchronization of new users.

The thesis is organized as follows: Chapter 2 introduces the multiple access systems in wireless communication and the Code Division Multiple Access systems in detail. It also discusses several proposed methods for optimum and sub-optimum multi-user decoding of signals at the base station for CDMA with short code sequence. Chapter 3 discusses several adaptive methods used in the literature and a comparison among them is made. In Chapter 4, the proposed adaptive decorrelating method along with the decision feedback cancellation structure is explained in detail. The the bit error rate of the new demodulator is theoretically calculated and it is shown that this enhances the near-far resistance capability of the receiver. Chapter 5 introduces several methods of synchronization for short chip sequence as it is used for adaptive decorrelating detector. It also discusses the influence on bit error rate due to the presence of new users during synchronization. The implementation of the simulations and the simulation results are discussed in Chapter 6, and Chapter 7 summarizes the work done and proposes future areas for research.

Chapter 2. Overview of Multiple Access Systems and DS-CDMA Multiuser Detector

In wireless communication systems, multiple access schemes are used to allow many mobile users to simultaneously share a finite amount of radio spectrum. The sharing of spectrum is required to achieve high capacity along with high quality of communications.

The three major access techniques used to share the available bandwidth in a wireless communication systems are frequency division multiple access (FDMA), time division multiple access (TDMA) and code division multiple access (CDMA). These techniques can be grouped into narrow and wideband systems, depending on the available bandwidth allocated to each user.

In conventional telephone systems, it is possible to talk and listen at the same time and this is known as duplexing. This feature is also required in wireless telephone system. Duplexing may be done using frequency or time domain techniques. Frequency division duplexing (FDD) provides two distinct bands of frequency for each user. A device called duplexer is used inside each mobile unit and base station to allow simultaneous radio transmission and reception on the duplex channel pair. Time division duplexing (TDD) uses time instead of frequency to provide forward and reverse link as shown in Figure 2.1. Thus TDD allows communication on a single channel and simplifies the subscriber equipment since a duplexer is not required.

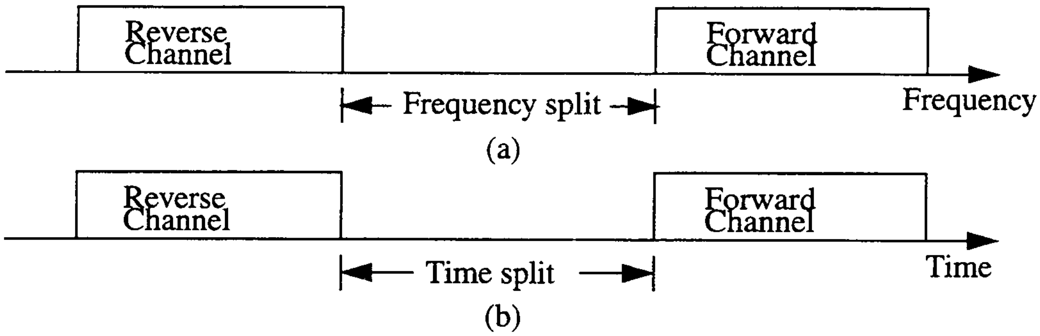


Figure 2.1 (a) FDD provides two simplex channels at the same time
(b) TDD provides two simplex time slots on the same frequency

The multiple access methods are described next.

2.1 Frequency Division Multiple Access (FDMA)

Frequency division multiple access (FDMA) assigns individual channels to each user. These channels are assigned on demand to the users and during the given call, no one else can use it. In FDMA-FDD system a pair of channels are assigned to each user, one channel to transmit and other channel to receive. The main features of FDMA are listed below.

- In FDMA, the bit rate is low and its period time is large. Here the channel delay has little effect on intersymbol interference (ISI). Hence, equalization is not used, in general, as intersymbol interference is relatively insignificant.
- FDMA is a continuous transmission scheme and it does not have overhead like synchronization.
- FDMA systems have higher cell site system cost, because of the single channel

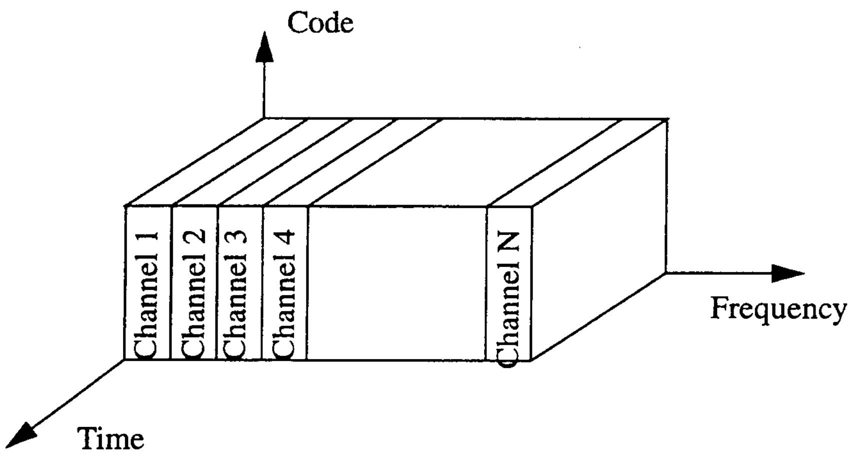


Figure 2.2 In FDMA different channels are assigned in different frequency bands

per carrier design and the need to use costly bandpass filter.

• FDMA uses a duplexer as it operates in FDD mode.

Figure 2.2 explains the basic principle of FDMA. In the late 1970s, Bell Laboratories developed the first US cellular telephone system call the Advanced Mobile Phone Services (AMPS). Similarly, the European Total Access Communication System (ETACS) was developed in mid 1980s and was virtually identical to AMPS. The salient features of AMPS and ETACS are given in Table 2.1 [1].

Table 2.1 AMPS and ETACS Radio Specifications

Parameter	AMPS Spec.	ETACS Spec.
Multiple Access	FDMA	FDMA
Duplexing	FDD	FDD
Channel Bandwidth	30 kHz	25 kHz
Traffic Channel per RF Channel	1	1

Table 2.1 AMPS and ETACS Radio Specifications

Parameter	AMPS Spec.	ETACS Spec.
Reverse Channel Freq.	824-849 MHz	890-915 MHz
Forward Channel Freq.	869-894 MHz	935-960 MHz
Voice Modulation	FM	FM
Peak Deviation: Voice Channel Control/Wideband Data	 +/- 12 kHz +/- 8 kHz	 +/- 10 kHz +/- 6.4 kHz
Channel Coding for Data Transmission	BCH(40,28) on FC BCH(48,36) on RC	BCH(40,28) on FC BCH(48,36) on RC
Data Rate on Control/ Wideband Channel	10 kbps	8 kbps
Spectral Efficiency	0.33 bps/Hz	0.33 bps/Hz
Number of Channels	832	1000

2.2 Time Division Multiple Access (TDMA)

Time division multiple access (TDMA) systems divide the transmission time into time slots as shown in Figure 2.3. In each slot only one user is allowed to either transmit or receive. Each user occupies a cyclically repeating time slot in a frame where the time slots for the number of total users (=N) comprise a frame. As the speaker is speaking continuously, transmitted data is stored in a buffer. During the time slot specified for given user the buffered data is transmitted in a burst mode. Thus in TDMA systems, transmission for any user is noncontinuous, implying, that TDMA can only be used in digital modulation. TDMA systems can use FDD or TDD modes of transmission. Each frame is made up of preamble, information message and trail bits. The preamble contains the address and synchronization information that both the base station

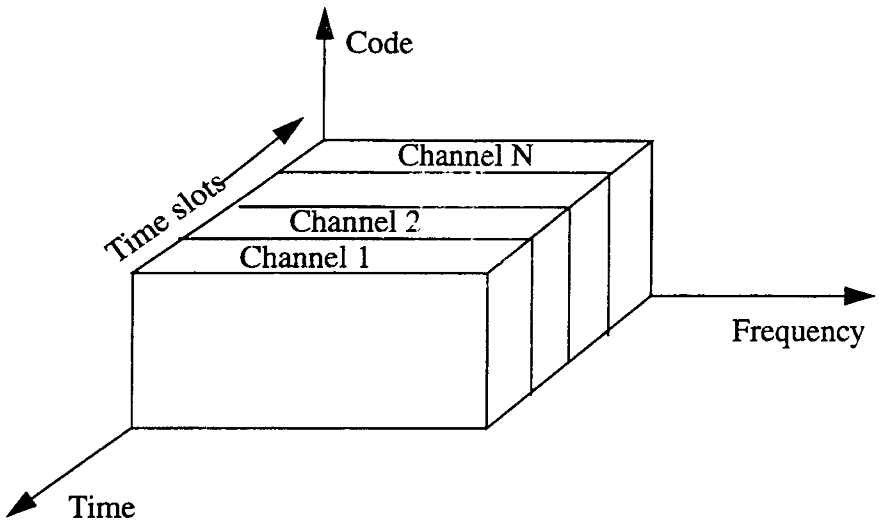


Figure 2.3 In TDMA scheme, each channel occupies a cyclically repeating time slot

and the subscribers use to identify each other. Guard times are utilized to allow synchronization of the receivers between different slots and frames. Different TDMA standards share the common features described briefly below [1]:

- In TDMA, a user shares a single carrier frequency with several users while using nonoverlapping time slots. The number of time slots depends upon modulation technique, available bandwidth etc.
- Data transmission in TDMA is noncontinuous. Hence the subscriber transmitter can be turned off when not in use, thus saving battery power.
- Adaptive equalization of channel is required as inter symbol interference is a major distortion.
- Due to buffer and burst mode of transmission, in each time slot, synchronization for each user is required. Also guard time is required to separate two successive time slots. Hence the synchronization and guard time are overhead in TDMA systems.

• Because of discontinuous transmission, the handoff process for a subscriber is simpler than FDMA. Handoff is the process of changing transmission from one base station to another base station, as the subscriber moves from one cell to another cell.

The first generation of analog AMPS system was not designed to support the current demand for capacity in large metropolitan areas. Cellular systems using digital modulation techniques offer large improvements in capacity and system performances. Global System for Mobile (GSM) - developed in Europe - is a second generation cellular system standard; it is the world's first TDMA cellular system to specify digital modulation, network level architecture and services. In the USA, after extensive research and comparison by major cellular manufacturers in the late 1980s, the United States Digital Cellular (USDC) System was developed using TDMA to support more users while sharing the same frequencies, reuse plan available by AMPS. For a smooth transition from AMPS to USDC, the interim standard IS-54 system was specified to operate using both AMPS and USDC standards (in dual mode) which makes roaming between the systems possible with a single phone. Table 2.2 summarizes the above mentioned two systems GSM and USDC (IS-54) [1].

Table 2.2 Second Generation Digital Cellular Standards Summary

	GSM	IS-54
Year of Introduction	1990	1991
Frequencies	890-915 MHz (R) 935-960 MHz (F)	824-849 MHz (R) 869-894 (F)
Multiple Access	TDMA/FDMA/FDD	TDMA/FDMA/FDD

Table 2.2 Second Generation Digital Cellular Standards Summary

	GSM	IS-54
Modulation	GMSK(BT=0.3)	$\pi/4$ DQPSK
Carrier Separation	200 kHz	30 kHz
Channel Data Rate	270.833 kbps	48.6 kbps
Number of Voice Channels	1000	2500
Spectrum Efficiency	1.35 bps/Hz	1.62 bps/Hz
Speech Coding	RELP-LTP @ 13 kbps	VSELP @ 7.95 kbps
Channel Coding	CRC with r=1/2; L=5 Conv.	7 bit CRC with r=1/2; L=6 Conv.
Equalizers	Adaptive	Adaptive
Portable Tx. Power Max./Avg.	1 W/ 125 mW	600 mW/200 mW

2.3 Spread Spectrum Multiple Access (SSMA)

Spread spectrum multiple access (SSMA) uses signals which have a transmission bandwidth that is several orders higher in magnitude than the minimum required RF bandwidth. A pseudo random noise (PRN) sequence is used to convert a narrowband signal to a wideband noise like signal before transmission. SSMA provides immunity to wireless channel rapid change also known as Rayleigh fading because of its wideband nature. Since many users can share the same bandwidth, SSMA systems are bandwidth efficient in a multiuser environment.

There are two main types of SSMA techniques: frequency hopped multiple access (FHMA) and direct sequence code division multiple access (DS-CDMA). They are described in the following section.

2.3.1 Frequency Hopped Multiple Access (FHMA)

Frequency hopped multiple access (FHMA) system is a digital multiple access system where the carrier frequency of the user is varied in a pseudo random fashion within a wideband channel [1]. In other words, the digital data is broken down into uniform sized bursts which are transmitted on different pseudorandomly chosen carrier frequencies. The instantaneous bandwidth of any transmission burst is much smaller than the total spread bandwidth. If the rate of change of the carrier frequency is greater than the symbol rate then that system is referred as fast frequency hopping system. If the channel changes at a rate less than or equal to the symbol rate, then the system is said to use slow frequency hopping. In the FHMA receiver, a locally generated PRN code is used to synchronize the receiver's instantaneous frequency to that of the transmitter. FHMA system may use narrowband FM or FSK modulation for transmission.

A frequency hopped system provides security because of the use of PRN sequence of frequency slots. In addition, FHMA is somewhat immune to fading when used with error control coding and interleaving as compared to DS-CDMA [1]. Error control coding is also useful to recover data when two or more users transmit on the same channel at the same time.

2.3.2 Direct Sequence Code Division Multiple Access (DS-CDMA)

In direct sequence code division multiple access (DS-CDMA) systems, the narrowband message signal is coded by a very large bandwidth spreading signal. The spreading signal is basically a pseudorandom code sequence that has a chip rate much greater than the data rate of the message. All users in DS-CDMA transmit data at the same time on the same spectrum as shown in Figure 2.1. Each user has its own spreading code and the codes are approximately orthogonal to other. The receiver, having knowledge of the transmitted code sequence, performs a time correlation operation between the received signal and the code to detect the transmitted data. Since the codes are orthogonal, all other users' transmitted data appear as noise due to decorrelation.

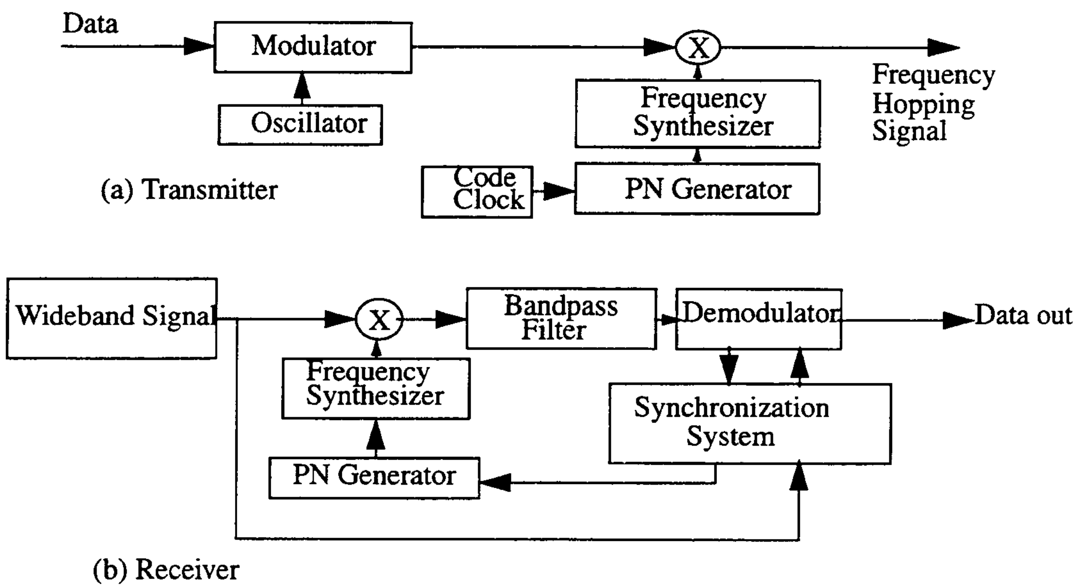


Figure 2.1 Block diagram of FH-CDMA system, a) transmitter and b) receiver

In DS-CDMA, the power of other existing users at a receiver determines the noise floor after decorrelation with the desired signal. In general, stronger received signal levels raise the noise floor at the base station, thus decreasing the probability that the weaker signals will be decoded correctly. This is known as near-far problem. To circumvent this problem, strict power control is used in the existing CDMA system (IS-95) [56]. Power control is asserted periodically by each base station in a cellular system and it assures that each mobile user within the base station coverage area provides approximately the same signal level to the base station receiver. The details of the near-far problem and the design of demodulators to alleviate the need for power control will be discussed in section 2.4 and 2.5. The features of the existing CDMA systems (based on the standard IS-95) include the following [2]:

- CDMA has a soft capacity limit. As the number of users in a CDMA system is increased, the noise floor is also increased in a linear manner with the increase in bit error rate.

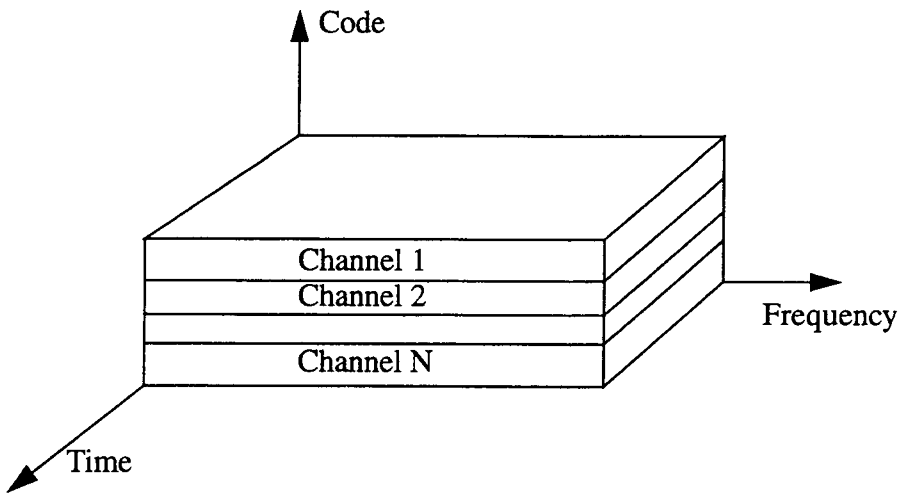


Figure 2.1 In CDMA, each channel is assigned a unique PRN code which is orthogonal to PRN codes used by other users

• The possible channel bandwidth in CDMA is greater than coherence bandwidth of the channel. Hence, the effect of multipath fading on the received signal will be less.

• Since the chip duration is very small, time delayed multipath components can be distinguished using the well known receiver known as RAKE receiver to reduce the bit error rate of the demodulator [1].

• Since CDMA uses the same spectrum in co-channel cells, soft handoff is possible in contrast to FDMA and TDMA. In the soft handoff process the mobile user moves from one cell to other without changing the carrier frequency or the spreading code.

A U.S. digital cellular system based on CDMA has been standardized as Interim Standard 95 (IS 95) by the U.S. Telecommunications Industry Association (TIA). Like IS-54, the IS-95 system is designed to be compatible with the existing U.S. analog cellular system (AMPS) frequency band for dual mode operation. In IS-95, user data changes in real time, depending on the voice activity and requirement in the system. The detail of IS-95 can be found in [56].

There are some inherent advantages and disadvantages of using CDMA over FDMA and TDMA [2] as discussed in the following section.

2.3.3 Advantages and disadvantages of CDMA

The spread spectrum technique has been long established for antijam and multipath rejection capability. Now in the form of direct sequence code division multiple access (DS-CDMA), it has been proposed to support simultaneous digital communication among a large community of relatively uncoordinated users. It has been recognized that DS-CDMA capacity is only interference limited unlike FDMA and TDMA, where capacities are primarily limited by bandwidth. CDMA takes advantage of the fact that voice signals are intermittent with a duty factor of 3/8. Hence CDMA capacity can be increased by 8/3 (or about 2) by suppressing transmission during the quiet period of each speaker [5].

Typically in terrestrial digital cellular systems, isolation among the cells is provided by path loss, which increases with the fourth power of distance [1]. Consequently, conventional techniques must provide different frequency allocation for contiguous cells (only reusing the same channel in one of every 7 cells in AMPS). However CDMA can reuse the spectrum for all cells, thus increasing capacity by a large percentage of normal frequency reuse factor. The capacity of the CDMA system can further be improved by using the common technique of sectorization and directional antennas per cell site both for receiving and transmitting [5].

It is well recognized that the time and frequency dependent fading effect of a channel degrades the signal. Since CDMA is a wideband system, its multipath fading is less severe [2]. It has also been mentioned that problems of intersymbol interference (ISI) and co-channel interference are less severe in CDMA than in TDMA.

The most important problem of CDMA is the near-far issue. In the conventional CDMA receiver, the desired user's signal is detected by correlating it with its spreading code. In this situation, other users' transmitted signals will form a interfering noise to the desired signal [6]. If some of the received signals are too strong compared to the weaker signals, the weak signals will have a very strong interfering component with high bit error rate. In the near-far problem, strong signal near the base station will block detection of far away weaker signals. IS-95 uses a power control method where the base station controls the transmit power of the mobile users to normalize the received signal strength. This puts a heavy burden on the power control to stop near-far problem from occurring.

In practical DS-CDMA applications, the channel is synchronous for communication from the base station to the mobile users (forward link). Here in the received signal, the bits of all users are aligned in time as the signals are transmitted from base station together. However, the channel will be asynchronous (i.e. bit signals are randomly delayed from one another) for the receiver at base station when the communication is from the mobile users to the base station (reverse link), because they are transmitted separately.

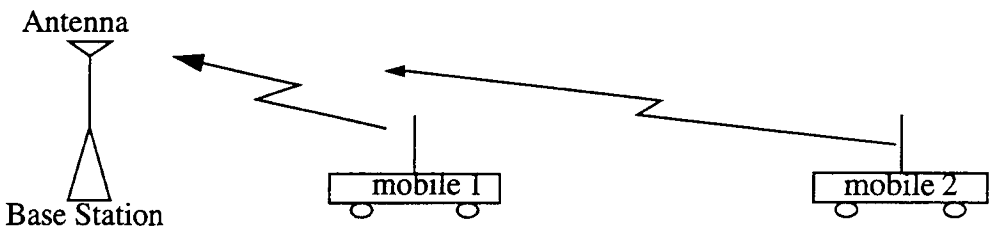


Figure 2.1 Near-far problem at the base station.

The near-far problem is a component of multiple access interference (MAI). MAI refers to the interference between DS-CDMA users at the receiver. This interference is the result of the asynchronous signal reception at the base station causing random time offsets between signals. This makes it impossible to design spreading codes which are perfectly orthogonal. A better detection strategy is multi-user detection, where, information about multiple users are used jointly to detect each individual user at the base station. The utilization of multi-user detection algorithms has the potential to solve not only the near far problem but also to provide additional benefits for DS-CDMA systems. The following sections contain a description of a transceivers structure of DS-CDMA including conventional detection and a literature survey that covers the existing multi-user detection methodologies.

2.4 Transceivers structure for DS-CDMA

In the direct sequence code-division multiple-access (DS-CDMA), all users in a communication channel uses different spreading codes while transmitting their individual signal. Now depending on whether mobile subscribers are transmitting or the base station is transmitting, two different transceivers structures can be formed. When the base station is transmitting to the mobile users, the signals for all the users are transmitted in phase and this is called synchronous transmission. As the spreading codes are designed to be almost orthogonal, simple conventional detector, discussed later, can be used for signal detection in the mobile hand-set. During transmission from the mobile subscribers to the base station, individual signal of a subscriber cannot be maintained in phase with that of other users. This results into the asynchronous transmission where the received signals of all the users in the communication channel are shifted from each other by unknown delays. At this situation the signals from each individual subscribers are not orthogonal to each other hence calls for a better method of detection, normally known as multi-user detection. In this thesis, the problem of better multi-user detection is considered. Figure 2.2 shows a transceivers structure where the mobiles are transmitting to the base station. In the following section, the conventional detector is discussed. This is the simplest of all receiver structures for DS-CDMA. This can be used as a single user receiver structure. All other structures which try to cancel the multiple access interference terms, generally work in multi-user mode. These are called multi-user detectors as they need information of all the users regarding their spreading codes and time delays to operate successfully.

Conventional Detection : In this section, a detailed mathematical description of a conventional detector is given. This discussion also clarifies the effect of multiple access interference [7][8]. For simplicity, a synchronous DS-CDMA channel is

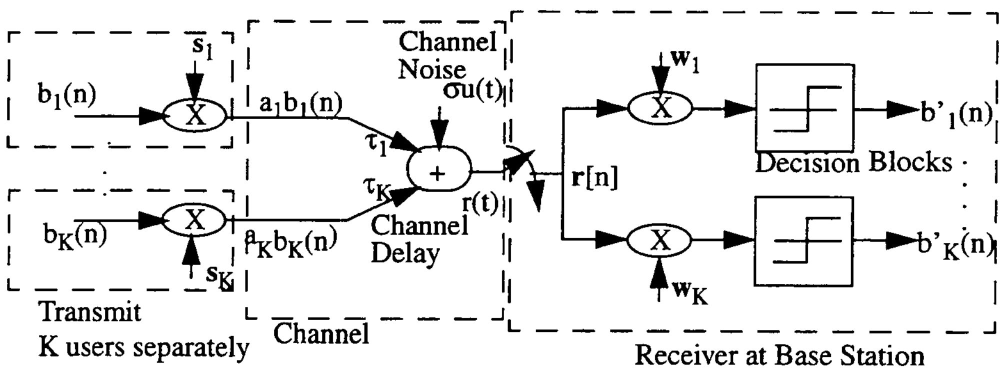


Figure 2.2 Transceivers structure for DS-CDMA system.

considered. To simplify the discussion, it is assumed that 1) all carrier phases are equal to zero, 2) each transmitted signal arrives at the receiver over a single path and 3) the data modulation is Binary Phase Shift Keying (BPSK). Figure 2.2 shows the synchronous transmission where the time delays (τ_1 to τ_k) introduced by the channel are considered as zero. Assuming there are K users in a synchronous single path BPSK real channel, the baseband received signal can be expressed as:

(1)

(2)

$$r(t) = \sum_{k=1}^{K} a_k(t) b_k(t)(s_k(t)) + \sigma u(t) \tag{3}$$

where, $b_k(t)$ is the binary transmitted data bit of the k^{th} user, $a_k(t)$ is the received strength of the signal, $s_k(t)$ is the k^{th} user spreading code and u(t) represents additive white gaussian noise (AWGN) with σ as the variance. The received power of the k^{th} signal is assumed to be constant over a bit interval. The modulation consists of rectangular pulses of duration T_b (bit interval), which takes on b_k = +/-1 values corresponding to the transmitted data. The signature code consists of rectangular pulses of duration T_c (chip interval), which takes on +/-1 values corresponding to some binary pseudo random code sequence. The chip rate is much higher than the bit rate, i.e. $T_c << T_b$. Multiplying the BPSK signal during transmission results in spreading the narrowband data signal to a wideband signal by a factor T_b/T_c (spreading factor). This factor is also called processing gain.

The conventional detector for the received signal is a bank of K correlators, as shown in Figure 2.3. First, the signature codes are used to decorrelate the received sig-

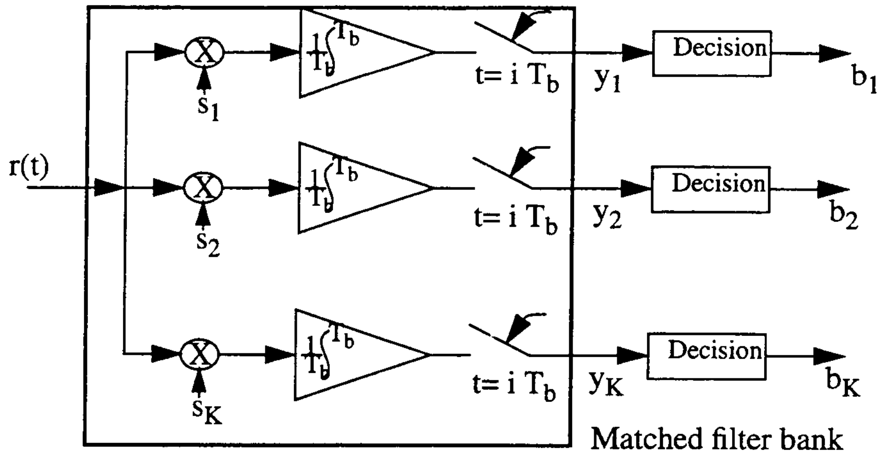


Figure 2.3 The conventional DS-CDMA detector: a bank of correlators with matched filters.

nal using matched filter consists of integrator for a bit period. The outputs of the correlators are sampled at the bit times yielding an estimates of the transmitted data bit along with its amplitude. This is known as soft estimate. The signs of the soft estimates form the hard decisions (+/-1). Hence, the conventional detector follows a single user detection strategy. The success of this method depends of the orthogonality of the signature codes.

Let the correlation value be defined as

$$\rho_{i,k} = \frac{1}{T_b}\int_{T_b} s_i(t)s_k(t)dt \qquad (4)$$

Here, $\rho_{k,k}=1$, otherwise $\rho_{i,k} \varepsilon [0,1)$. The output of the matched filter for k^{th} user over a particular bit interval is

$$y_k = \frac{1}{T_b} \int_{T_b} r(t) s_k(t) dt \tag{5}$$

$$y_k = a_k b_k + \sum_{i=1, i \neq k}^{K} \rho_{i,k} a_i b_i + \frac{1}{T_b} \int_{T_b} \sigma u(t) s_k(t) dt \tag{6}$$

The desired signal is $a_k b_k$. The interference from the other users MAI_k is $\sum_{i=1, i \neq k}^{K} \rho_{i,k} a_i b_i$ and the resultant noise is $\frac{1}{T_b} \int_{T_b} \sigma u(t) s_k(t) dt = z_k$. Decoding the received signal, with k^{th} user signature code gives the recovered data, multiple access interference (MAI) term and the noise term z_k. The existence of MAI has a significant impact on the capacity and performance of the conventional direct sequence system. MAI power increases linearly with the increase in number of users and it depends on the amplitude of the received signals of other users. Hence, an interferer with a higher amplitude will make detection of a weaker signal harder, thus creating the near-far problem. This problem can also arise due to fading. During fading individual signal in asynchronous DS-CDMA will fluctuate constantly depending on the mobile velocity and reflected paths. It will be possible that when most of the received signals are strong, few others are weak due to fading, creating near-far problem. The objective of this thesis is to develop a near-far resistant multi-user receiver for asynchronous DS-CDMA communication systems which is immune to the multiple access interference.

Research efforts directed at mitigating the effect of MAI on conventional detectors have focused on the multiuser detection. In the following section different multi-user detectors will be discussed, each of which fall into one of three categories.

Non-recursive detectors: These are mainly the linear detectors. Here a linear mapping is applied to the outputs of the conventional detectors (matched filter outputs) to cancel the MAI term present [10]-[15]. These can be divided into three broad categories: the decorrelating detector, the minimum mean squared error (MMSE) detector and decision feedback detector. In the above mentioned detectors, the correlation matrix is formed using the matched filter output. In the decorrelating detector, the inverse of the correlation matrix is used to cancel MAI terms in the matched filter output and to get estimate of the amplitudes and bits for all users. In the MMSE detector, noise power and received amplitudes of all users are considered along with the correlation matrix for inversion to multiply to the matched filter output. In Both the methods, noise gets enhanced. In the decision feedback detector, the correlation matrix is broken down into lower triangular matrix using Cholesky decomposition algorithm [53]. This is multiplied to the matched filter output and in this case noise does not get enhanced. Following this, successive interference cancellation is done. In the following section on multi-user detection, the above mentioned methods will be discussed in detail.

Recursive detectors: These are the adaptive implementation of the linear detectors. This circumvents the use of matrix inversion present in linear detectors and works under minimum mean squared error criteria. This includes adaptation with and without (blind adaptation) training sequence [30]-[35]. In Chapter 3, different adaptive algorithms are considered which are the least mean square (LMS), the recursive least square (RLS) and the linearly constraint constant modulus (LCCM) adaptive algorithms.

Subtractive interference cancellation: Here the amplitude and bit estimates of the stronger users are used to regenerate the signals for those users and subtracted out of the received signal leaving the weaker signal with less interference. This can be further divided into successive interference cancellation (SIC) and parallel interference cancellation (PIC) [17]-[19]. Successive Interference Cancellation scheme requires amplitude estimation for all the users and using that information to take decision about the strongest user. Following that it regenerate the signal for the strongest user and cancel it from the received signal producing the input for the next stage. This repeats to take the decisions for all the users. In case of parallel interference cancellation, several stages are used for the correct estimation of bit. In each stage, the bits are estimated using matched filter and following that using amplitude estimates the signals are regenerated. The regenerated signals are used to form the interference term for each user and subtracted from the received signal to create clean signals with less MAI for the next stage. These clean signals are used to estimate bits in the next stage of PIC.

In the following section on multi-user detection, all the methods are discussed in detail.

2.5 Multi-User Detection

Recently there has been a great interest in improving DS-CDMA detection through the use of multi-user detectors. In multi-user detection, code and timing information of multiple users are jointly used to detect an individual user.

Verdu's work [8], proposed and analyzed the optimal multiuser detector. This detector is known as the maximum-likelihood sequence (MLS) detector as it is developed on Maximum Likelihood criteria. The problem with the MLS approach is that there are 2^K possible choices of bit in synchronous transmission and 2^{NK} possible choices in asynchronous transmission where K stands for number of users and N is the message length. However, the MLS detection can be implemented for DS-CDMA by following the correlator bank with a Viterbi algorithm. Unfortunately, the required Viterbi algorithm also has a complexity that is exponential in the number of users, i.e., 2^K for asynchronous case. Another disadvantage of MLS detector is that it requires knowledge of the received amplitudes a_k and the time delays (τ_k) which must be estimated [8].

For multi-user detection, it will be convenient to introduce the matrix-vector notation of the system model to describe the output of the conventional detector. In a synchronous channel, the received signals are aligned in time. Here, the detection can focus on one bit interval independent of other transmitted bit neglecting the multi-path fading. For three users as shown in Figure 2.4, output of the conventional detector for one bit can be given as:

$$y_1 = r^*s_1 = a_1b_1 + \rho_{2,1}a_2b_2 + \rho_{3,1}a_3b_3 + z_1 \quad (7)$$

$$y_2 = r^*s_2 = \rho_{1,2}\, a_1b_1 + a_2b_2 + \rho_{3,2}a_3b_3 + z_2 \quad (8)$$

$$y_3 = r^*s_3 = \rho_{1,3}\, a_1b_1 + \rho_{2,3}\, a_2b_2 + a_3b_3 + z_3 \quad (9)$$

This can be written in matrix form as

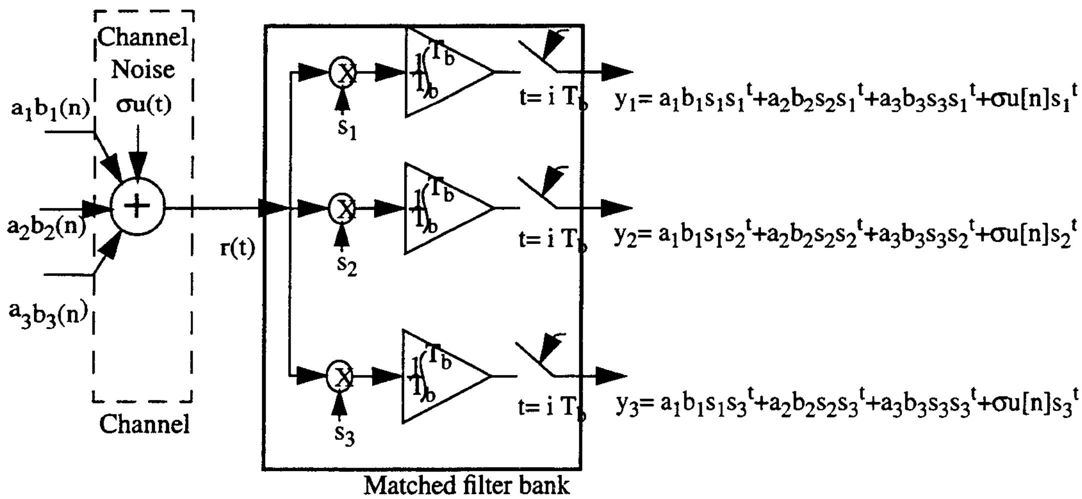


Figure 2.4 Matched filter output for 3 users synchronous DS-CDMA.

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} = \begin{bmatrix} 1 & \rho_{2,1} & \rho_{3,1} \\ \rho_{1,2} & 1 & \rho_{3,2} \\ \rho_{1,3} & \rho_{2,3} & 1 \end{bmatrix} \begin{bmatrix} a_1 & 0 & 0 \\ 0 & a_2 & 0 \\ 0 & 0 & a_3 \end{bmatrix} \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix} + \begin{bmatrix} z_1 \\ z_2 \\ z_3 \end{bmatrix} \tag{10}$$

or,

$$\mathbf{y} = \mathbf{RAb} + \mathbf{z} \tag{11}$$

For a K-user synchronous system, **y**, **b** and **z** will be vectors of dimension K with correlator output, transmitted data bits and noise term. **R** and **A** will be matrices with dimension of K x K with correlation and amplitude information. Since, $\rho_{k,i} = \rho_{i,k}$, the matrix **R** is symmetric. It is possible to break **R** into two matrices: one presenting the autocorrelation (**I**) and the second for crosscorrelation (**Q**) where **Q** contains off-diagonal terms only. Then the conventional matched filter output (10) can be written as:

$$\mathbf{y} = \mathbf{Ab} + \mathbf{QAb} + \mathbf{z} \tag{12}$$

where, the second term **QAb** represents the MAI present in the conventional detector output. It will shown later that in multi-user case, this allows perfect MAI cancellation.

The problem of detection in asynchronous channel is more complex than in a synchronous channel. The transmission from mobile subscribers to the base station is asynchronous since each signal is received by the base station at different time due to the different delay paths associated with each user.

The continuous time model of a received signal for synchronous transmission can be modified for single path asynchronous channel as:

$$r(t) = \sum_{n=-N}^{N} \sum_{k=1}^{K} a_k(t) b_k(t + nT - \tau_k) s_k(t - \tau_k) + \sigma u(t) \tag{13}$$

where τ_k is the delay of the k^{th} user. The matrix model of asynchronous transmission similar to Eq. *11* should encompass the entire message.

For an example, a multiuser system is considered where only three users are present and each of them is transmitting three bits as shown in Figure 2.5. Here each user bit is delayed by a fraction of a bit period τ_k from other. The output of the conventional detector can be formed using Eq. *11* where it will be considered as nine users transmitting one bit over a time period of $(3T + \tau_3 - \tau_1)$. Then the correlation matrix **R** can be written as:

$$\boldsymbol{R} = \begin{bmatrix} 1 & \rho_{2,1} & \rho_{3,1} & 0 & 0 & 0 & 0 & 0 & 0 \\ \rho_{1,2} & 1 & \rho_{3,2} & \rho_{4,2} & 0 & 0 & 0 & 0 & 0 \\ \rho_{1,3} & \rho_{2,3} & 1 & \rho_{4,3} & \rho_{5,3} & 0 & 0 & 0 & 0 \\ 0 & \rho_{2,4} & \rho_{3,4} & 1 & \rho_{5,4} & \rho_{6,4} & 0 & 0 & 0 \\ 0 & 0 & \rho_{3,5} & \rho_{4,5} & 1 & \rho_{6,5} & \rho_{7,5} & 0 & 0 \\ 0 & 0 & 0 & \rho_{4,6} & \rho_{5,6} & 1 & \rho_{7,6} & \rho_{8,6} & 0 \\ 0 & 0 & 0 & 0 & \rho_{5,7} & \rho_{6,7} & 1 & \rho_{8,7} & \rho_{9,7} \\ 0 & 0 & 0 & 0 & 0 & \rho_{6,8} & \rho_{7,8} & 1 & \rho_{9,8} \\ 0 & 0 & 0 & 0 & 0 & 0 & \rho_{7,9} & \rho_{8,9} & 1 \end{bmatrix} \tag{14}$$

where $\rho_{i,k}$ is the partial crosscorrelation between i^{th} and k^{th} bits. For K users in asynchronous transmission and each users transmitting N bits, the matrix **R** will have a dimension of NK x NK.

Most of the proposed multi-user detectors can be classified roughly as non-recursive, recursive and subtractive interference cancellation detectors as mentioned earlier. In the following sections they will be discussed in detail.

2.5.1 Non-Recursive Detectors

The optimum detector reviewed in the beginning of section 2.5 provides important performance gains over the conventional single-user detector, including the solution of the near-far problem. The price is an increase in implementation costs, in particular, the exponential complexity of the decision algorithm in the number of users and the need to acquire the actual values of the received signal amplitudes.

The next important group of multi-user detectors are linear multi-user detectors [10]-[15]. These detectors apply a linear mapping, **L** to the output of the conventional detector to reduce the MAI seen by each user. These are also known as decorrelating detector, since these detectors decorrelates the interference terms from the matched filter output leaving only the desired user's component. The decorrelating detector was initially proposed by Schneider [13] and then was extensively studied by Lupas and Verdu [10]. The decorrelating detector for synchronous channel was extended for asynchronous channel [11]. At first the situation will be examined when the demodulator is constrained to ignore the received amplitudes of the active users.

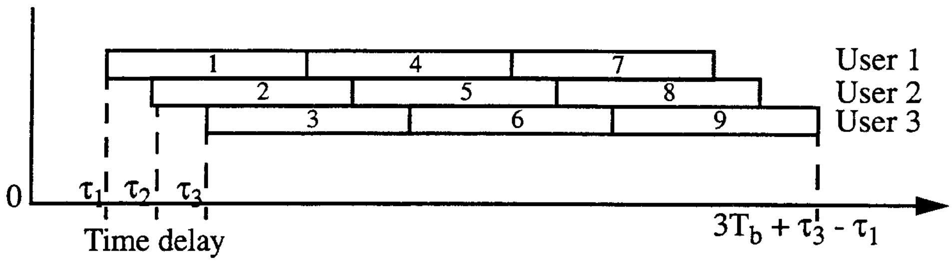


Figure 2.5 Sample timing diagram for an asynchronous channel.
There are 3 users and 3 bits per users

2.5.2 Decorrelating Detectors

Synchronous channel: The most likely bits and amplitudes are those that best explain the received waveform in a mean-square sense, that is, the error $\varepsilon^2(t)$ will be

$$min\ a_k \in |0, \infty\rangle\ \ min\ b \in (-1,1)^K \int_0^T \left[r(t) - \sum_{k=1}^{K} a_k b_k s_k(t) \right]^2 dt \tag{15}$$

If y denotes the matched filter outputs, then the product term inside the integral can be written in matrix form as:

$$r^2(t) - 2c^t y + c^t Rc \tag{16}$$

where $c_k=a_k b_k$, so $\mathbf{c}^t=[c_1\ c_2\ .....\ c_K]$ and $\mathbf{R}$ is the correlation matrix with elements,

$$\rho_{ij} = \int_0^T s_i(t) s_j(t) dt \tag{17}$$

Now minimization of Eq. *15* is equivalent to maximization of

$$max...c \in R^K[2c^t y - c^t Rc] \tag{18}$$

with respect to **c**. If the matrix **R** is invertible, from the solution of Eq. *18* the best estimate of **c** is **c***, where

$$\mathbf{c^*=R^{-1}y} \tag{19}$$

and the most likely bits are given by,

$$\mathbf{b} = \text{sgn}\ (\mathbf{c^*}) = \text{sgn}\ (\mathbf{R^{-1}y}) \tag{20}$$

and $|\mathbf{c}^*| = \mathbf{a}$ where $\mathbf{a}^t = [a_1\ a_2 \ldots a_k]$.

The decorrelating detector reforms the matched filter outputs to a linear transform prior to threshold comparison and completely eliminates MAI. This method has the following attractive properties. The decorrelating detector provides substantial performance and capacity gain over conventional detector. This method reforms the maximum likelihood sequence detector when the amplitudes of all users are not known. Thus, it does not need the estimate of the received amplitudes. The most attractive property is that the decorrelating detector has computation complexity linear with the number of users. For synchronous transmission, this can decorrelate one bit at a time.

A disadvantage of the decorrelating detector is that it increases noise floor by $\mathbf{R}^{-1}\mathbf{z}$. Furthermore, to implement this detector, all the active users' spreading codes, their bit timings are needed and it requires inversion of the matrix **R** which for synchronous transmission is of dimension K x K where K is the number of users and for asynchronous transmission, is of dimension NK x NK, where N is the message length. For the asynchronous case, inverting the correlation matrix **R** is more difficult. There are suboptimal approaches to implement the decorrelating detector by breaking up the detection problem into more manageable blocks, even to one bit transmission interval [11][16].

2.5.3 Minimum Mean Square Error (MMSE) Detector

The minimum mean-squared error (MMSE) detector is also a linear detector which trades off suppression of multiuser interference with noise reduction when the signal amplitudes are known by the receiver [14]. The problem of MMSE detection can be set as follows: let the matched filter output **y** be given as **y** = **RAb** + **Sn** = **Rd** + **Sn**, where **R** is the correlation matrix, **d** =**Ab**, **S** = $[s_1 \ldots s_K]^t$, $s_k=[s_{1,k} \ldots\ldots s_{L,k}]^t$, **n** is a Gaussian random variable with variance σ and L is the length of the chip sequence. Now the vector **d** is also considered as a random variable taking values between $(\infty, -\infty)$. Now the best estimate of **d** can be given by, $\hat{d} = E(dy^t)[E(yy^t)]^{-1}y$ [58]. Let $\hat{d} = Ly$, then **L** is known as the linear transformation required to get the best estimate of **d**.

$$\text{Now } E(\mathbf{dy}^t) = E(\mathbf{dd}^t\mathbf{R}^t + \mathbf{b}\,\mathbf{n}^t\mathbf{S}^t) = E(\mathbf{dd}^t)\,R^t = \mathbf{A}^2\mathbf{R}^t$$

$$\text{Also, } E(\mathbf{yy}^t) = E((\mathbf{Rd}+\mathbf{Sn})(\mathbf{d}^t\mathbf{R}^t + \mathbf{n}^t\mathbf{S}^t)) = \mathbf{R}\,E(\mathbf{dd}^t)\,\mathbf{R}^t + \mathbf{S}\,E(\mathbf{nn}^t)\,\mathbf{S}^t$$

$$= \mathbf{R}\,\mathbf{A}^2\,\mathbf{R}^t + \sigma^2\,\mathbf{R}^t$$

$$\text{So,} \quad \mathbf{L} = \mathbf{A}^2\,\mathbf{R}^t/(\mathbf{R}\,\mathbf{A}^2\,\mathbf{R}^t + \sigma^2\,\mathbf{R}^t) = [\,\mathbf{R} + \sigma^2\mathbf{A}^{-2}]^{-1} \qquad (21)$$

Because it takes into account the background noise, the MMSE detector generally provides better probability of error performance than the decorrelating detector. As the background noise goes to zero, the performance of the MMSE detector converges to the decorrelating detector. The disadvantages of the MMSE detector are that it needs to invert the matrix R and also requires the amplitude estimate of the received signals [14].

2.5.4 Decision-Feedback (DF) Detector

Duel-Hallen first reported the decision feedback (DF) detector (also known as zero-forcing decision feedback or decorrelating decision feedback) [24]. It performs two operations: first, linear preprocessing on the received signal which partially decorrelates the matched filter output without enhancing the noise. Second, an SIC operation, which takes decision and subtracts out the interference from one additional user at a time, in descending order of signal strength. Figure 2.1 explains the basic operation of decision feedback detector for synchronous CDMA.

In synchronous CDMA, a white noise model can be obtained by factoring the positive definite matrix of cross-correlations as $\mathbf{R} = \mathbf{F}^t\,\mathbf{F}$, where, $\mathbf{F}$ is a lower triangular matrix using Cholesky decomposition algorithm. If the filter with response $(\mathbf{F}^t)^{-1}$ is applied to the sampled output of the matched filter, the resulting output vector is

$$\hat{y}_d = FAb + n \tag{22}$$

where n is a white noise vector with the autocorrelation matrix $\mathbf{R}(\mathbf{n})=\sigma^2\mathbf{I}$ ($\mathbf{I}$ is K x K identity matrix). The model in Eq. *22* gives rise to the decorrelating decision feedback detector. The kth component of $\hat{y}_d$ is given by

$$\hat{y}_{d,k} = F_k a_k b_k + \sum_{i=1}^{k-1} F_{k,i} a_i b_i + n_k \tag{23}$$

Here it is assumed that the amplitudes of the users are in decreasing order, that is, $A_1 > A_2 > \ldots > A_K$. Since, the expression in Eq. *23* does not contain a MAI term, a decision for this user is made first: $b_1 = \mathrm{sgn}\,(\hat{y}_1)$. The MAI term in y_2 is from b_1. Since a decision for the first user is available, one can use feedback in estimating the second user's data bit. Similarly for kth user, the MAI depends on all users' amplitudes stronger than itself. As decisions for these users have already been made, they can be used to form a feedback term (shown in Figure 2.1),

$$\hat{b}_k = \mathrm{sgn}\left(\hat{y}_i - \sum_{i=1}^{k-1} F_i a_i b_i\right) \tag{24}$$

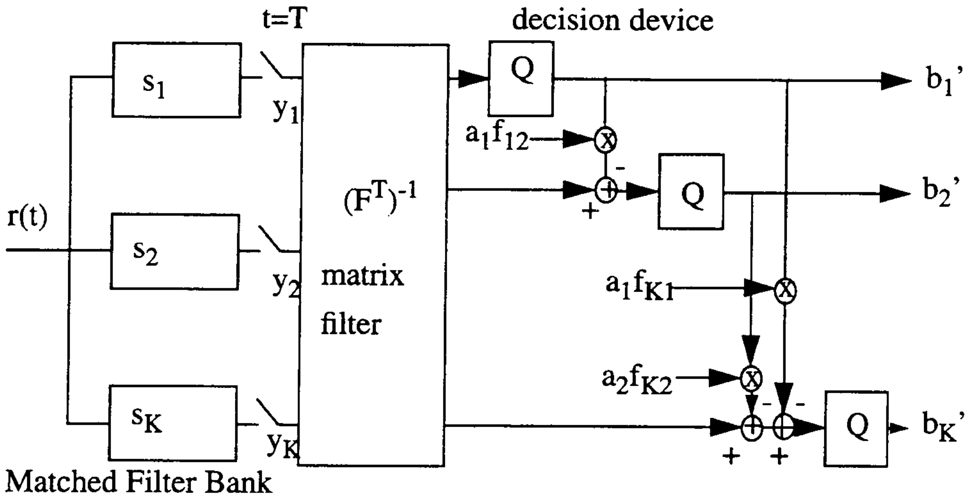


Figure 2.1 Matched filter receiver and decorrelating decision feedback detector for synchronous DS-CDMA

Similar to the derivation for synchronous system, decision feedback detector for asynchronous system has also been proposed [23][25]. Like the synchronous case, there is feedforward filter and unlike synchronous case there is a feedback filter too.

Under the assumption that all past decisions are correct, the decision feedback detectors eliminate all MAI and maximizes the signal to noise ratio [23]. An important difficulty in DF detector is the need to compute Cholesky decomposition and the whitening filter $(F^t)^{-1}$ (matrix inversion). The DF detectors like the subtractive interference cancellation detectors, has the additional disadvantages of needing to estimate the received signal amplitudes. If the soft outputs of the decorrelating detector are used to estimate the amplitudes, the DF detector is equivalent to the decorrelating detector [23]. If the amplitude estimates are better, the DF detector has better performance than decorrelating detector. However, if the estimates are less reliable, the DF detectors performs worse than the decorrelating detector [7].

2.5.5 Recursive Detectors

The development of multiuser detection is proceeding along a path which is typical of other areas in communications. Initially, optimum solutions were obtained along with the best possible performance achievable in Gaussian noise channel. Those results showed a huge gap between the optimum performance and the performance of the conventional single user detector. In particular, they showed that the near-far problem is not a flaw of CDMA but the inability of the conventional receiver to exploit the structure of the multiple access interference.

The second stage in the development of multiuser detection was devoted to the analysis and design of detectors that could achieve significant performance gains over the conventional receiver without incurring the exponential complexity of optimum detector. This brought the nonrecursive detectors already discussed and subtractive interference cancellation detectors to be mentioned in the next section. Motivated by the channel environments encountered in many CDMA applications, the design of multiuser detectors also has started for channels with Rayleigh fading, frequency selective fading and multipath time dispersive fading.

The foreground multiuser detectors depend on various parameters such as received amplitudes and cross-correlations which are not fixed and known beforehand. Therefore, the recent thrust in research in multi-user detection is the design of adaptive detectors which self-tune the detector parameters from the observation of the received waveform.

2.5.6 The adaptive linear MMSE detector

The adaptive linear MMSE detector was first proposed in [30]. Further work has been done on it modifying main algorithm [31]-[33]. Significant speed up is also achieved using the recursive least square (RLS) algorithm [34][35]. The minimum mean-square error detector (MMSE) mentioned previously tries to find a linear transform L in Eq. *21* to the matched filter outputs (**y**) by minimizing $E[|\mathbf{b} - \mathbf{L}\mathbf{y}|^2]$. The contribution of the k^{th} user to the penalty function $E[|\mathbf{b} - \mathbf{L}\mathbf{y}|^2]$ is equal to $E[(b_k - <\mathbf{c}_k,\mathbf{y}>)^2]$ where the linear transform is denoted by $\mathbf{c}_k$. The gradient of the cost function inside the expectation is equal to $2\,(<\mathbf{c}_k,\mathbf{y}> - b_k)\mathbf{y}$. Because of the convexity of the penalty function, the gradient descent adaptive algorithm is formed as:

$$c_k[n] = c_k[n-1] - \mu(\langle c_k[n-1], y[n]\rangle - b_k)y[n] \tag{25}$$

This will converge with infinitesimally small step size μ to the argument that minimizes the penalty function. The following information is required for implementation of the above mentioned algorithm:

- The training sequence of the desired user must be known.
- The timing of the desired user must be acquired.
- The signature waveform of the desired user facilitates the initialization of the algorithm.
- It can be implemented in synchronous and asynchronous channel.

2.5.7 Blind adaptive multi-user Detection

The requirement of training sequences in the multiuser detectors mentioned above is cumbersome in multiuser communications. Recently a blind adaptive multiuser detector is reported which requires considerably less information for operation [36][37][48],

- It requires the knowledge of the signature coefficient of the desired user.
- It requires the timing of the desired user.

The blind multiuser detector adapts a linear transformation of the observations whose impulse response is c_k for k^{th} user and outputs the decision:

$$\hat{b}_k = \mathrm{sgn}(\langle y, c_k \rangle) \tag{26}$$

$\mathbf{c}_k$ can be written in canonical orthogonal decomposition: $\mathbf{c}_k = \mathbf{s}_k + \mathbf{x}_k$ where $\langle \mathbf{s}_k, \mathbf{x}_k \rangle = 0$. The energy of the output of the linear transformation $\langle \mathbf{y}, \mathbf{s}_k + \mathbf{x}_k \rangle$ has three additive components: the first due to the desired user, the second due to the MAI and the third due to the background noise. The first component is transparent to the choice of $\mathbf{x}_k$. Thus variation in $\mathbf{x}_k$ can only change the energy of the second and third components. Accordingly, a very simple strategy is chosen for x_k that minimizes the output energy: $\mathrm{MOE}(\mathbf{x}_k) = E[(\langle \mathbf{y}, \mathbf{s}_k + \mathbf{x}_k \rangle)^2]$. This can also be written as $\mathrm{MOE}(\mathbf{x}_k) = E[(A_k b_k - \langle \mathbf{y}, \mathbf{s}_k + \mathbf{x}_k \rangle)^2] + A_k^2$. Thus the MOE solution for $\mathbf{x}_k$ is also the solution for the MMSE linear detector. Therefore minimization of the $\mathrm{MOE}(\mathbf{x}_k)$ lends the blind adaptation rule which is guaranteed to converge globally [37],

$$x_k[n] = x_k[n-1] - \mu Z[n](y[n] - Z_{MF}[n]s_k) \quad (27)$$

where $Z_{MF}[n]=<y[n], s_k>$ and $Z[n]= <y[n], s_k + x_k[n-1]>$. In the asynchronous case, it is possible to work with signals that span one bit, or, in order to improve performance we can lengthen the duration of the linear transformation. As usual, it is possible to improve convergence rate by the recursive least square adaptation method.

2.5.8 Subtractive Interference Cancellation

The third class of multi-user detectors can be grouped as subtractive interference cancellation detectors. The basic principle of these detectors is to estimate the MAI contributed by each user and subtract the interference from the output received signal. Such detectors are used in multiple stages to improve the detection. Some of these detectors are also known as decision feedback detectors, as they are similar to feedback equalizers for inter-symbol interference (ISI) cancellation.

The signal decision in this method can be 'hard' or 'soft'. The soft-decision approaches use the soft decisions, that is, the amplitudes of the detected signal to estimate the amplitude and data bit. Thus these tends to be linear in contrast to the 'hard' decision based detectors. The hard decision based approach feeds back a bit decision and is nonlinear.

In this section, an overview of two subtractive interference cancellation (successive and parallel) detectors is given [17][18].

2.5.9 Successive Interference Cancellation (SIC)

The first SIC structure was reported in [19]-[21], where it was used as the demodulator stage in addition to the adaptive antennas. The SIC scheme is further investigated [22] for BPSK and M-ary orthogonal modulation.

The successive interference cancellation detectors consists of K stages for K number of total users, taking a successive cancellation approach to cancel interference. The first stage of the cascaded multi-stages is shown in Figure 2.1. In the first stage of this detector the hard decision about the transmitted bit is made for the strongest user among all the users. The estimate of the amplitude of the same user is used to regenerate that signal and cancels out that user from the received signal. Thus the signal after stage-1 can be given by $r_1(t) = r(t\text{-}T_b) - a_1(t\text{-}T_b)b_1s_1(t\text{-}T_b)$. So, the remaining users see less MAI in the next stage. Similarly in the second stage, the hard decision for the transmitted bit of the next strongest user is made. Using its amplitude estimation, the signal of that user is generated and cancelled out from the output of the first stage. Thus the signal after stage-2 will be $r_2(t) = r_1(t\text{-}T_b) - a_2(t\text{-}2T_b)b_2s_2(t\text{-}2T_b)$. This continues for detecting all the users. Before SIC is used, all the users should be ranked according to their received amplitude strength. The operation of k^{th} stage can be summarized as : 1)detect the strongest signal using a conventional detector and take a hard decision, 2) with the knowledge of its PN sequence and estimated timing and amplitude, regenerate the signal and 3) subtract the regenerated signal from the received signal $r_k(t)$ of the previous stage and thus create the cleaned version of the received signal $r_{k+1}(t)$

The output of each stage is the decision on the strongest user and a modified received signal. Thus in multistage, decision are taken for all users. The reason for cancelling the signals in descending order of signal strength are twofold. First, the correct data decision is the best for the strongest user in presence of all other users. Second, cancellation of the strongest user provides the most benefit to the other remaining users as the MAI from the strongest user is no longer present.

The implementation of SIC is simple in concept but requires additional hardware to take into account the delay in each SIC stage. Also, each time the profile of the amplitude strength of users changes, reordering of the users needs to be done. The most important problem in SIC is if the amplitude estimate of the strongest user in any stage (or in the earliest stages) is wrong. Then instead of MAI cancellation, MAI for the strongest user gets doubled in amplitude and quadrupled in power.

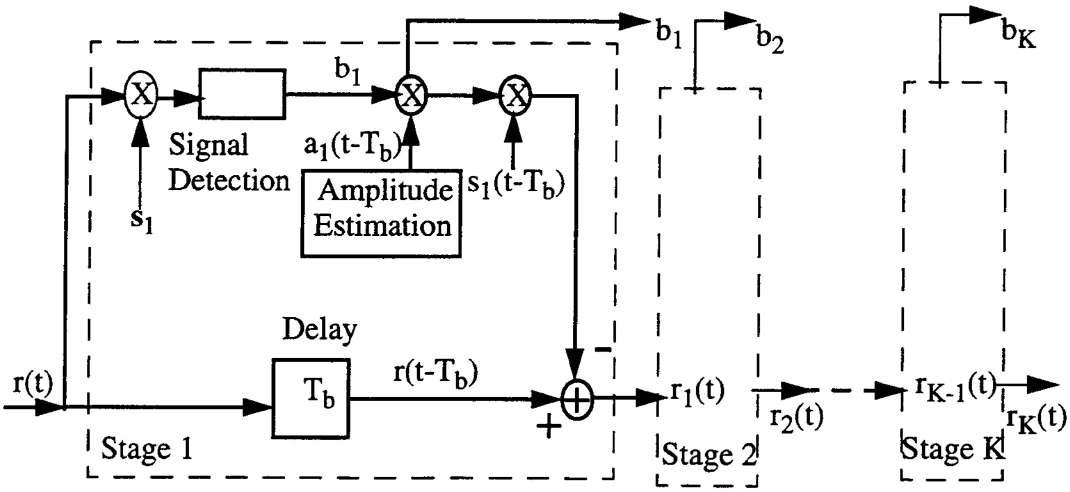


Figure 2.1 The multi-stage SIC detection.

2.5.10 Parallel Interference Cancellation (PIC)

The multistage PIC structure was introduced by Varanasi et al [26]. Also, application of the basic PIC structure is found in [20]-[21]. A survey on the PIC methods is provided in [17]. In PIC method, it is assumed that the amplitude estimate of all the users are known. In each stage of a multi-stage PIC, first the hard decision of the transmitted bit for each users are made. Then after regenerating the signal from the estimated bits, amplitudes and spreading codes of all users, the interference component for a user by all other users are found out. This interference term is then cancelled from the received signal to get the clean signal for every user. In the next PIC stage, these clean signals are used for bit estimation. Normally matched filters are used for bit estimation.

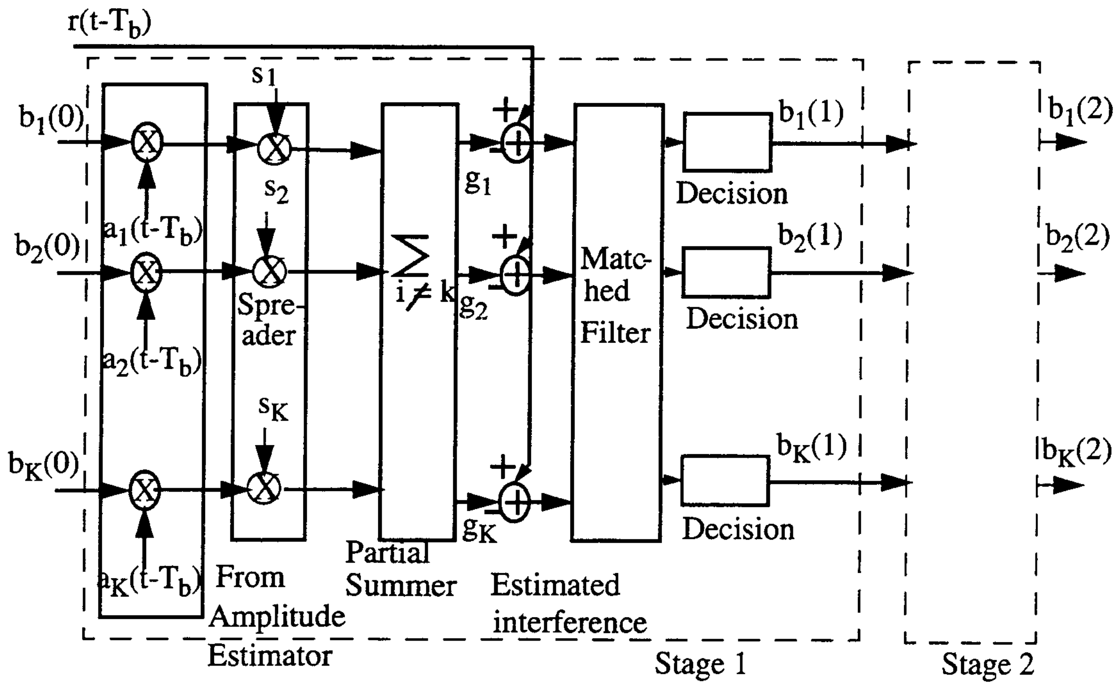


Figure 2.1 PIC detector with hard decision.

A single stage of the PIC detector structure is shown in Figure 2.1 which is part of multi-stage PIC detector. Here in every stage hard decisions are considered. The initial data bit estimates, **b**(k), are derived from a matched filter detector. These bits are then scaled by the amplitude estimates and regenerated using the known spreading codes, which produces the delayed estimate of the MAI in the received signal for the k^{th} user. After subtracting the estimated MAI (g_k) from the received signal r(t),

$$r(t-T)-g_k = b_k a_k s_k(t-\tau_k-T_b)+\sigma u(t-T_b)+\sum_{i\neq k}^{K}(b_i-\hat{b}_i)a_i s_i(t-\tau_i-T_b) \tag{28}$$

where, g_k is the calculated interference term for k^{th} user by all other users. The result is passed through a matched filter for each user to produce a better estimate of the data bit. This process can be repeated for multiple stages.

Some of the existing PIC structures are discussed below:

The performance of the PIC detector depends heavily on the initial data estimates [26]. Therefore, using the decorrelating detector as the first stage significantly improves the performance of the PIC detector [27].

It is also possible to use the already detected bits at the output of the current stage to improve detection of the remaining bits in the same stage [25]. Thus the most up-to-date decisions are used. This detector is referred to as a multistage decision feedback detector. The initial stage could be a decision feedback detector, the conventional detector or the decorrelating detector.

It has been reported that a partial MAI cancellation in each stage, with the amount of cancellation increasing for each stage, is the most powerful of the subtractive interference cancellation [29].

Comparison between SIC and PIC:

It is found that when all the users are received with equal strength, the parallel interference cancellation method outperforms the successive interference cancellation scheme. When the received signals are of distinctly different strength (the more important Rayleigh fading case), the SIC scheme is superior in performance than the PIC method. The important thing to note is that in both cases, both (SIC and PIC) outperform the conventional detector [18].

2.6 Performance of Multi-User Detectors

In the previous section, various multi-user detection methods were discussed which mainly take care of the near-far problem in asynchronous DS-CDMA. This section considers the performance of those multi-user detectors. It is observed that though it is possible to have an optimum detector (solution of maximum likelihood criteria) for asynchronous DS-CDMA systems using Viterbi detector it is not possible to implement it for a large number of users (> 10) present in a system, since it requires 2^K states in Viterbi detector for K users[8]. Also the optimum solution requires knowledge of the amplitude for each user. The decorrelating detector, which does not require amplitude information, is an optimum solution for both synchronous and asynchronous transmission. But for asynchronous transmission the decorrelating detector requires matrix inversion of size NK X NK, where K is the number of users and N is the message length [9]-[10]. The minimum mean square error detector requires amplitude estimation, as well as, matrix inversion of same size as the decorrelating detector [14]. The decision feedback detector requires Cholesky decomposition of the decorrelating matrix [23]-[24]. Thus all the non-recursive methods although are optimum or near optimum, are not implementable in real time communication system.

The recursive detector mainly uses minimum mean square error criteria to derive the recursive algorithm [48]. The recursive detectors thus produced use the least mean square and the recursive least square adaptive algorithm [30]-[35]. Recently a recursive algorithm has been developed from nonlinear optimization which is known as the linearly constraint constant modulus algorithm [50]. All of the above mentioned algorithms use short code and although they are suboptimum, they are implementable in real time communication system with varying degree of hardware complexities depending on the algorithm chosen. Due to this reason, in Chapter 3, the above mentioned important multi-user adaptive methods are reviewed.

The subtractive interference cancellation schemes are implementable (minimum hardware complexity), but their performance is not comparable to the recursive or non-recursive detectors. The simulation results on parallel interference cancellation shows that maximum number of users is half of the processing gain and for a signal power 6 dB less than the maximum signal power [57]. The bit error rate (BER) found are far worse than the BER for a single user in additive white Gaussian noise (AWGN).

For successive interference cancellation, the simulation results reported are for number of users one half of the processing gain. The reported BER is quite poor compared to the single user case under AWGN [22]. Thus the recursive algorithms show the best performance in terms of bit error rate with higher hardware complexity.

For less number of users present in the system, adaptive multiuser shows perfect multiple access interference cancellation. However, as the number of users in the system increases, beyond a point, the adaptive system can only partially cancel the multiple access interference term. Due to this problem, adaptive multi-user detector loses the near-far resistance. To cancel the MAI term completely, a new method is proposed. In this new method, the converged tap-coefficients of adaptive algorithm are used along with subtractive cancellation scheme. Since in this proposed method, the subtractive scheme uses the soft estimates (the amplitude and bit), the overall system remains linear. This subtractive cancellation scheme is discussed in Chapter 4 in detail. Also the theoretical bit error rate of the proposed method is calculated in that Chapter with and without Rayleigh fading in presence of additive white Gaussian noise.

Thus in the proposed method, recursive multi-user detection is combined with the subtractive interference cancellation scheme to get a overall superior performance, which is practically implementable. The subtractive scheme used is different from the existing PIC and SIC methods.

Chapter 3. Recursive Interference Cancellation

In this chapter the adaptive decorrelating detector is discussed as a viable option for replacing the linear decorrelating detector for synchronous and asynchronous DS-CDMA. As discussed in the last chapter, the linear decorrelating detector requires on line real time inversion of large matrices. Instead, the adaptive system uses simple recursive structure such as the least mean square (LMS) adaptation to cancel interference. First, the LMS algorithm is presented for interference cancellation in the presence of channel fading and without fading. Other adaptive processes considered in this chapter are the recursive least square (RLS) algorithm and the linearly constrained constant modulus algorithm (LCCMA). The performance of these two algorithms are compared with the LMS algorithm. The linear minimum mean squared algorithm will be studied first, as most of the adaptive detectors are implementing it adaptively.

3.1 Minimum mean squared error Detector

The linear decorrelating detector, as mentioned in chapter 2, has many advantages. But the main disadvantage is that it causes noise enhancement. An alternative liner detector, the minimum mean square error (MMSE) detector, takes this into account. Given $\mathbf{y}[n]$ the matched filter output, the objective of the MMSE detector is to find the transformation $\mathbf{L}$ which cancel the interference present in $\mathbf{y}[n]$. This is done by minimizing the error,

$$\varepsilon = E\left[|\mathbf{b} - \mathbf{L}\,\mathbf{y}|^2\right] \qquad (29)$$

where, **b** is the data vector and **y** is the matched filter output as explained in section 2.4. This error can be minimized with respect to **L** as shown in section 2.5 to get,

$$L_{MMSE} = \frac{1}{[\boldsymbol{R} + \sigma^2 A^{-2}]} \tag{30}$$

Thus the linear MMSE has the features of the decorrelating detector, except that it requires knowledge of the received amplitudes. If the background noise level or the k^{th} user received energy dominates, then the MMSE detector approaches the conventional single user matched filter. If the background noise level vanishes, the MMSE detector approaches the decorrelating detector [7].

The great advantage of the linear MMSE detector is the simplicity in converting it to adaptive algorithm using training sequences and adaptive FIR filter. The detail of the adaptation process is explained below.

The LMS algorithm normally uses a training sequence to adapt the tap coefficients which cancels the MAI present in the demodulated desired signal. The training sequence is normally transmitted from the transmit end, thus in the received signal it is present along with other users' signals. The same training sequence is also known to the receiver and using that information, the adaptive process finds the tap coefficients ($\mathbf{w}_k$) which are used to demodulate signal. In presence of a new user, all the existing users also need to retrain the tap coefficients. The LMS algorithm is implemented by a bank of finite impulse response (FIR) filter along with the algorithm to change the tap coefficients. For each user, a separate adaptation process is required at the base station which

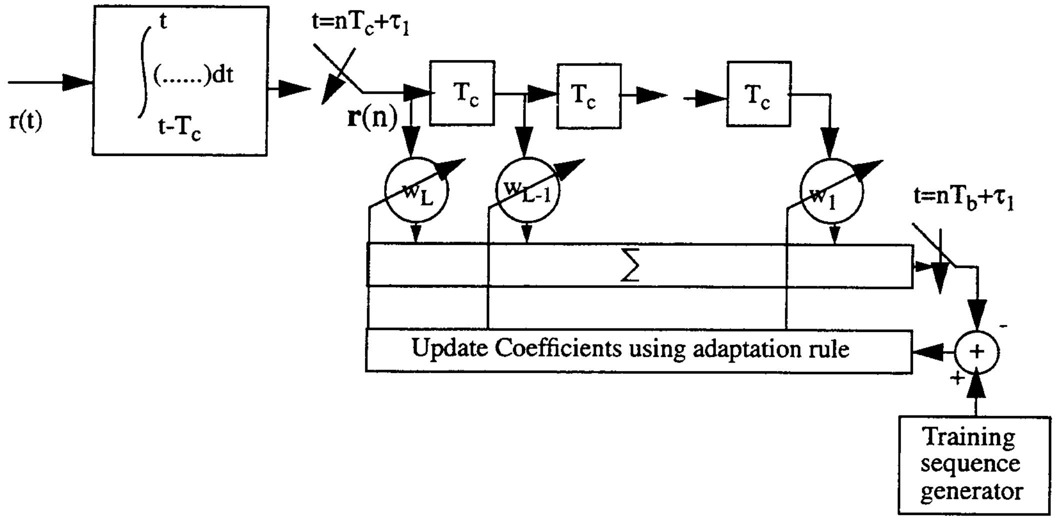


Figure 3.1 The MMSE receiver at baseband

works for all in parallel in presence of a new user. The demodulation for the desired k^{th} user's bit is done by correlating adapted tap coefficients $\mathbf{w}_k$ with the received signal $\mathbf{r}[n]$,

$$\hat{b}_k(n) = \mathrm{sgn}\left(w_k r^t(n)\right) \tag{31}$$

The structure of the adaptive filter is shown in Figure 3.1. It consists of a FIR filter with adjustable tap weights whose value for n^{th} bit period and for k^{th} user is given by $\mathbf{w}_k(n)=[w_1(n)\ \ w_2(n)\ .....\ w_L(n)]$. Here, L denotes the length of chip sequence and equal for one bit period. Here, the number of taps equals to L.

During initial tap adjustment process, an additional signal d(n), the training sequence, is supplied along with the usual received signal. This training sequence provides a frame of reference for adjusting the tap coefficients ($\mathbf{w}_k$) of the FIR filter. The vector of the tap inputs at bit period n is denoted by $\mathbf{r}(n)=[r_1(n)\ r_2(n)\ ....\ r_L(n)]$. By comparing the estimate ($\mathbf{w}^t{}_k(n)\mathbf{r}(n)$) with the desired response d(n), an estimation error e(n) is produced. Thus, the estimation error, $e(n) = d(n) - \mathbf{w}^t{}_k(n)\mathbf{r}(n)$. The objective of the adaptive algorithm is to minimize this estimation error in mean square sense such that it results into the decorrelating coefficients $\mathbf{w}_k$ and provides best estimate of d(n).

If the input vector $\mathbf{r}(n)$ and the desired response d(n) are jointly stationary, the mean squared error J(n) (= $E[|e(n)|^2]$) at the n^{th} bit period is the quadratic function of the tap-weight vector which can be written as [53],

$$J(n) = \sigma^2{}_d - \mathbf{w}^t{}_k(n)\mathbf{p} - \mathbf{p}^t\mathbf{w}_k(n) + \mathbf{w}^t{}_k(n)\mathbf{R}\mathbf{w}_k(n) \tag{32}$$

where, $\sigma^2{}_d$ is the variance of the desired response d(n), $\mathbf{p}$ is the cross-correlation vector between the tap-input vector $\mathbf{r}(n)$ and the desired response d(n) ($\mathbf{p} = E[\mathbf{r}(n)d(n)]$) and $\mathbf{R}$ is the correlation matrix of the tap-input vector $\mathbf{u}(n)$ ($\mathbf{R} = E[\mathbf{r}(n)\mathbf{r}^t(n)]$).

The dependence of the mean-squared error J(n) on the elements of the tap-weight vector $\mathbf{w}_k(n)$ as a bowl-shaped surface with a unique minimum. The adaptive process is continually seeking the bottom or the minimum point of this surface [53]. At the minimum point of the error-performance surface, the tap-weight vector takes on the optimum value $\mathbf{w}_{o,k}$, which is defined by the normal equation $\mathbf{R}\mathbf{w}_{o,k} = \mathbf{p}$ and the minimum mean-squared error equals to $J_{min} = \sigma^2{}_d - p^t\mathbf{w}_{o,k}$.

Differentiating the mean-squared error, J(n) with respect to the tap-weight vector $\mathbf{w}(n)$:

$$\nabla(n) = \frac{\partial}{\partial w(n)} J(n) = -2p + 2Rw(n) \tag{33}$$

and the updating of the tap-weight vector is done as,

$$w(n+1) = w(n) + 0.5\mu[-\nabla(n)] \tag{34}$$

The simplest choice of the estimate of **R** and **p** is to use the instantaneous estimate that are based on sample values of the tap-input vector **u**(n) and the desired response d(n). Then the estimate of **R** is given by $\mathbf{R}_e(n)=\mathbf{u}(n)\mathbf{u}^t(n)$ and the estimate of **p** is given by $\mathbf{p}_e(n)=\mathbf{u}(n)d(n)$. Correspondingly, the gradient vector will be of the form:

$$\hat{\nabla}(n) = -2r(n)d(n) + 2r(n)r^t(n)\hat{w}(n) \tag{35}$$

Now substituting this into the updating of the tap-weight vector, the LMS algorithm is given by,

$$\hat{w}(n+1) = \hat{w}(n) + \mu r(n)\left[d(n) - r(n)\hat{w}^t(n)\right] \tag{36}$$

Then the minimum mean squared error is equal to, as mentioned earlier, $J_{min} = \sigma^2_d - p^t\mathbf{w}_{o,k}$ and the tap weight error vector for the LMS algorithm can be given as, $\varepsilon_k(n) = \hat{w}_k(n) - w_{o,k}$. where, $\mathbf{w}_{o,k}$ defines the optimum Weiner solution for the tap-weight vector [53].

Ideally, the minimum mean squared error J_{min} is realized when the tap-weights $\mathbf{w}_k(n)$ of the FIR filter approaches the optimum value $\mathbf{w}_{o,k}$ defined by the normal equation. But as the LMS algorithm relies on an estimate for the gradient vector, it results in a tap-weights estimate which approaches $\mathbf{w}_{o,k}$ after a large number of iterations and then fluctuates about $\mathbf{w}_{o,k}$. In terms of tap-weight error vector, ε(n), we may express the mean-squared error, J(n), as $J(n) = J_{min} + \varepsilon^t(n)\mathbf{R}\varepsilon(n)$. Then the average mean-squared error, E[J(n)], converges to a steady state value if the step size parameter μ satisfies the condition [53],

$$0 < \mu < 2/(\text{ total input power}) \tag{37}$$

So for a stationary input the total input power equals $L\rho(0)$ where L is the number of taps and $\rho(0)$ is the autocorrelation function of the tap inputs.

The LMS adaptation using MMSE rule requires the following information when applied for DS-CDMA: 1) the training sequence must be known to the receiver, but the signature waveforms of the interfering users need not be known to find each user's adapted coefficients $\mathbf{w}_k$, 2) the timing of the desired user must be acquired, whereas the timing of the interfering users need not be acquired and 3) knowledge of the signature waveform of the desired user in not necessary, but helps the initialization of the algorithm.

In order to understand the capabilities and limitations of LMS adaptation completely, it is necessary to specify in a more quantitative manner how the desired signal and interference manifest themselves in terms of the FIR filter coefficients at steady state [31]. Let $\mathbf{w}_k(i) = [w_0(i)\ w_1(i)\ w_2(i)........w_{L-1}(i)]$ be the vector of tap weights after the i^{th} update for kth user and let the vector $\mathbf{r}(i) = [r_0(i)\ r_1(i)\ r_2(i)........r_{L-1}(i)]$ represent the contents of the delay line at time $t = iT_b$. The decision statistic for i^{th} data is given by $z(i)=\mathbf{w}_k(i)\mathbf{r}^t(i)$. Let $d_k(i)$ be the i^{th} data bit and let $\mathbf{s}_k=[s_{k,0}\ s_{k,1}\ s_{k,2}.....\ s_{k,L-1}]$ be one period of the spreading sequence for the k^{th} user. Then the content of the equalizer at the i^{th} sampling time is given by (assuming user-1 is the desired user) [31]:

$$u(i) = a_1 s_1 d_1(i) + \sum_{k=2}^{K+1} a_k I_k d_k(i) + n(i) \tag{38}$$

where, $I_k(i) = s_k^{(m)}$ if $d_k(i-1) = d_k(i)$, $I_k(i) = s'^{(m)}_k$ if $d_k(i-1) = -d_k(i)$ and

$$s_k^{(m)} = [s_{k,L-m}\ s_{k,L-m+1} \cdots\cdots s_{k,L-1}\ s_{k,0}\ s_{k,1}\ s_{k,2} \cdots\cdots\cdots s_{k,L-m-1}]; \tag{39}$$

$$s'^{(m)}_k = [-s_{k,L-m}\ -s_{k,L-m+1} \cdots\cdots -s_{k,L-1}\ -s_{k,0}\ s_{k,1}\ s_{k,2} \cdots\cdots\cdots s_{k,L-m-1}]; \tag{40}$$

and $\mathbf{n}(i)$ is a vector of independent Gaussian random variables with zero mean and variance of σ^2. The delays (the τ_k) can be written as $\tau_k = m\, T_c$ where the delays have been considered as multiple of chip duration.

Any adaptive equalizer which minimizes mean-squared error must choose its tap weights to be the solution to the normal equation [53],

$$\mathbf{Rw_1 = p} \tag{41}$$

where, $\mathbf{R}$ is the autocorrelation matrix of the equalizer contents, E $[\mathbf{r}^t(i)\ \mathbf{r}(i)]$, and $\mathbf{p}$ is the correlation between the desired response and the equalizer contents, E $[d_1(i)\ \mathbf{r}(i)]$. The expected values imply an averaging over those quantities which vary with time (the data and noise sequence), while τ_k is considered fixed for the k^{th} user in the given system. From Eq. *38*, it is seen that [31],

$$\mathbf{p} = a_1 \mathbf{s}_1 \tag{42}$$

and

$$R = a_1^2 s_1^t s_1 + \sum_{k=2}^{K+1} a_k^2 E\left[I_k^t(i) I_k(i)\right] + \sigma^2 I_N \tag{43}$$

The average of the outer product of the interference terms takes the form

$$E\left[I_k^t(i) I_k(i)\right] = \frac{1}{2} s_k^t s_k + \frac{1}{2} s'^t_k s'_k \tag{44}$$

The tap coefficients which gives the solution to the normal equation Eq. *41* are given by

$$\mathbf{w}_1 = \mathbf{R}^{-1}\mathbf{p}; \tag{45}$$

Now under steady state condition when there is no fading, a_k is held constant and thus **R** is a constant. Under these circumstances, one can find $\mathbf{w}_k$ which will be used for cancelling the MAI. Under steady state condition and no Rayleigh fading of channel, the minimum mean-squared error, J_{min}, of the adaptive receiver can be given by [31],

$$J_{min} = 1 - \mathbf{s}_1 \mathbf{w}^t_1 \tag{46}$$

The probability of error of the receiver can be related to J_{min} by invoking a Gaussian approximation to the resultant interference plus noise which passes through the adaptive receiver. Then, under this Gaussian approximation, the probability of error is given by [31]:

$$P_e = Q\left(\sqrt{\frac{1}{J_{min}}}\right) \tag{47}$$

where Q(x) is the standard Gaussian integral

$$Q(x) = \int_{x}^{\infty} \exp\left(-\frac{t^2}{2}\right) dt \qquad (48)$$

In presence of Rayleigh fading the correlation matrix of the input vector $\mathbf{r}(n)$ becomes,

$$R = E\left(a_1^2 s_1^t s_1\right) + \sum_{k=2}^{K+1} E\left[a_k^2 I_k^t(i) I_k(i)\right] + \sigma^2 I_N \qquad (49)$$

So $\mathbf{R}$ will be dependent on the amplitudes a_k which are Gaussian random variables. Under Rayleigh fading the LMS adaptation does not reach the steady state solution previously obtained when the fading rate of channel is substantial in compare to the convergence of the LMS algorithm. The LMS algorithm may diverge when the step size μ does not satisfy the condition given in Eq. *37*. To circumvent this nonconvergence problem, normalized least mean square (NLMS) algorithm can be applied under fading condition. The adaptation equation (derived from Eq. *36* and Eq. *37*) for NLMS algorithm is given by,

$$w(n+1) = w(n) + \frac{\mu_{NLMS}}{\|u(n)\|^2} u(n)[d(n) - w^t(n)u(n)] \qquad (50)$$

where, $\|\mathbf{u}(n)\|^2$ is the tap-input vector power. Eq. *36* and Eq. *37* are merged to form the NLMS algorithm except that here μ_{NLMS} is a constant term between 0 and 2 and $\|u(n)\|^2$ is the input vector power changing all the time. But even NLMS algorithm will not converge to the steady state solution of the LMS adaptation under Rayleigh fading

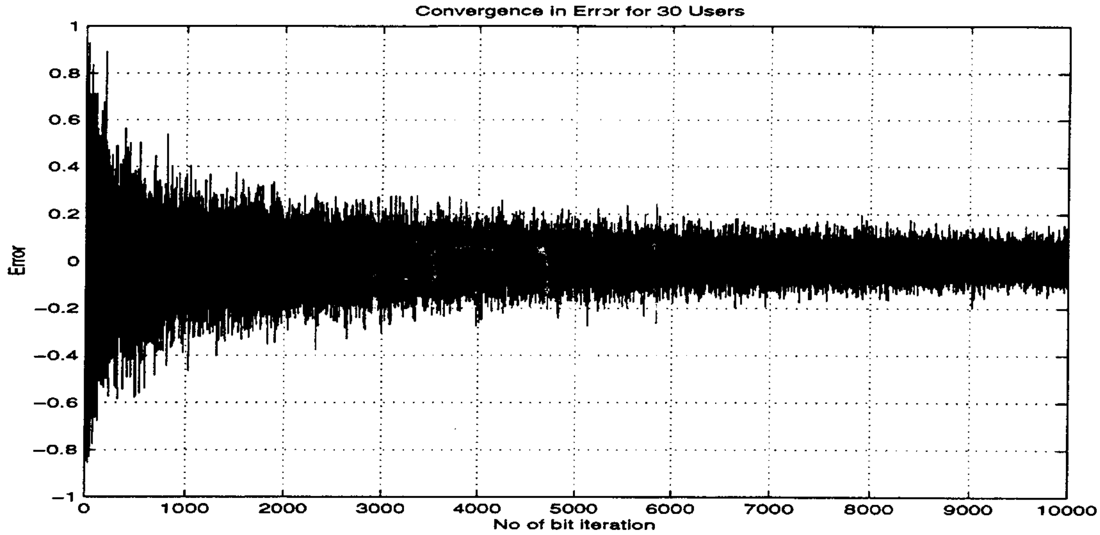


Figure 3.2 Convergence on error term using the least mean squared adaptation with 30 users present in the system

condition. The simulation is carried out using LMS adaptation to get the adapted coefficients for 30 users present in the asynchronous DS-CDMA system. The Figure 3.2 shows the convergence of error e(n) with number of bit iteration. The Gold code of length (L) 63 is considered to spread the data bits of each user.

The convergence of gradient based LMS algorithm is very slow, especially when the eigen values of the input covariance matrix R have a very large spread [1]. In order to achieve fast convergence, complex algorithms based on least square approach are used. Here the rapid convergence relies on error measures expressed in terms of a time average of the actual received signal instead of statistical average as used in LMS algorithm.

In the following section, usage of the recursive least square adaptive algorithm for asynchronous DS-CDMA is discussed.

3.2 Recursive least squared algorithm

In the least square algorithm the error is defined by $e(i,n) = d(i) - w_k^t(n)r(i)$ and the conjugate of error is given by $e^*(i,n)$. Here, **r**(i) is the input vector at time i and the $\mathbf{w}_k(n)$ is the new tap coefficients at time n for k^{th} user. e(i,n) is the error using the new tap gain at time n to test the old data at time i. The least square error based on the time average is defined as [1],

$$J(n) = \sum_{i=1}^{n} \lambda^{n-i} e^*(i,n)e(i,n) \tag{51}$$

where λ is the weighting factor close to 1, but less than 1, and J(n) is the cumulative squared error of the new tap coefficients on all the old input vectors.

The least squared solution requires finding $\mathbf{w}_k(n)$ the tap coefficients of the FIR filter such that the cumulative squared error J(n) is minimized. It uses all the previous data to test the new tap coefficients. The parameter λ is the weighting factor that weights the recent input vector u(n) more heavily in computation, so that J(n) tends to forget the old data in a nonstationary environment. Hence it is also called the forgetting factor.

To obtain the minimum of least square error J(n), the gradient of J(n) is set to zero. This results in the equation, $R(n)\hat{w}_k(n) = p(n)$ where, $\hat{w}_k(n)$ is the optimal tap coefficients for the k^{th} user [1] and

$$R(n) = \sum_{i=1}^{n} \lambda^{n-i} u^t(i)u(i) \tag{52}$$

$$p(n) = \sum_{i=1}^{n} \lambda^{n-i} d(i)u(i) \tag{53}$$

The recursive formulation of the least squared algorithm can be formed as [1],

$$\hat{d}(n) = \boldsymbol{w}^{t}(n-1)\boldsymbol{u}(n) \tag{54}$$

$$e(n) = d(n) - \hat{d}(n) \tag{55}$$

$$\boldsymbol{k}(n) = \frac{[\boldsymbol{R}^{-1}(n-1)\boldsymbol{u}(n)]}{\lambda + \boldsymbol{u}^{t}(n)\boldsymbol{R}^{-1}(n-1)\boldsymbol{u}(n)} \tag{56}$$

$$\boldsymbol{R}^{-1}(n) = \frac{1}{\lambda}[\boldsymbol{R}^{-1}(n-1) - \boldsymbol{k}(n)\boldsymbol{u}^{t}(n)\boldsymbol{R}^{-1}(n-1)] \tag{57}$$

$$\boldsymbol{w}(n) = \boldsymbol{w}(n-1) + \boldsymbol{k}(n)\overset{\circ}{e}(n) \tag{58}$$

The weighting factor λ does not change the rate of convergence of the adaptation, but does determine the tracking capability of the adaptation in non-stationary environment.

The requirements of the recursive least squared (RLS) algorithm to work are 1) the training sequence for the desired user must be known, 2) the timing of the desired user must be acquired and 3) the signature code of the desired user helps in initialization.

The simulation is carried out using the RLS adaptive method for asynchronous DS-CDMA system with 30 users present in the system. The Gold code of length 63 is used for spreading the data bits for each user. The Figure 3.3 shows the convergence in error e(n) with increase in number of bit iteration.

Recently another algorithm has been applied for getting the multi-user adaptive receiver in synchronous DS-CDMA communication. This algorithm is called linearly constraint constant modulus algorithm which has an advantage that it can work without training sequence. Also it performs better when the amplitudes of the individual user's are changing constantly like in fading [50]. This will be explained in detail in the following section.

3.3 The constant modulus algorithm

The constant modulus algorithm (CMA) has two desirable properties that set it apart from the adaptive techniques like LMS and RLS adaptation [50][51]. The CMA adapts blindly and hence it does not need any reference or training sequence. Secondly the CMA can be used in multipath environment as it restores back the constant envelope property of the received signal. The main CMA algorithm is given below.

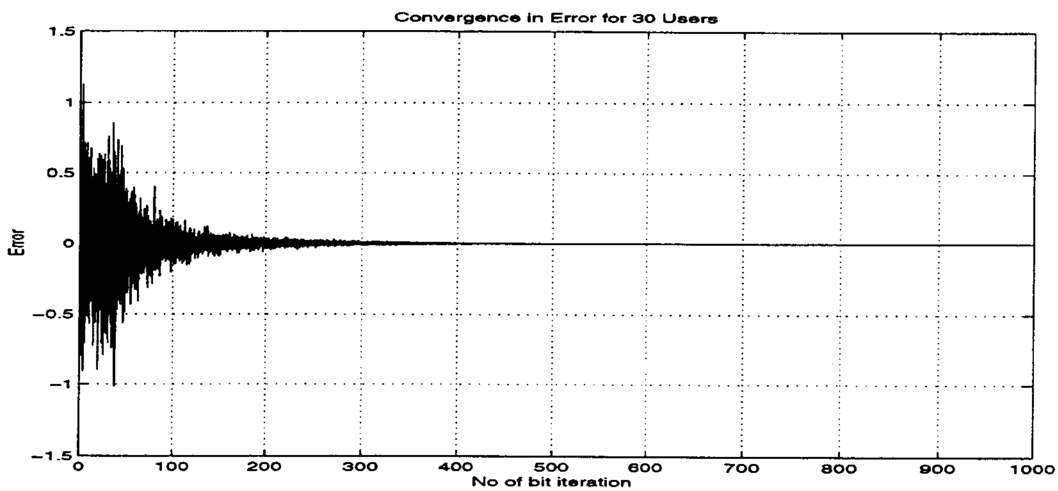


Figure 3.3 Convergence on error term using the recursive least squared adaptation with 30 users present in the system

The output y(n) of the constant modulus algorithm is written as $y(n)=\mathbf{w}^t(n)\mathbf{u}(n)$, where $\mathbf{u}(n)$ is the input vector and $\mathbf{w}(n)$ is the tap coefficients (t symbolizes the transpose). The goal of the CMA processing is to find a weight vector $\mathbf{w}$ that minimizes fluctuation in the envelope of the output y(n). Accordingly, the first step is to define a cost function J that measures how far the output is from a constant modulus state. One such function which has been used in literature is [51],

$$J = \frac{1}{4}\langle(|y|^2 - \delta)^2\rangle \tag{59}$$

This cost function J simply measures the average variation of the envelope from an arbitrary constant value of δ. The constant modulus algorithm iteratively solves for the minimum by using an approximation of the gradient descent approach. The gradient approximation is found by dropping the expectation operators < . > and then calculating the gradient ∇ with respect to w which is $\nabla w = (|y|^2 - \delta)y^t u$. This instantaneous gradient is then substituted into the standard gradient descent iteration to yield the constant modulus algorithm,

$$w(n+1) = w(n) - \mu(|y(n)|^2 - \delta)y^t(n)u(n) \tag{60}$$

There is a problem with this cost function J. Any output that is constant modulus is a minimum of J. In practice this means that CMA can null the signal of interest and capture some other constant modulus signal instead [51]. It can be controlled in some instances by manipulating the initial conditions and the signal environment. In the next section, a method is presented that offers much greater control over the behavior of the algorithm [50].

3.4 The linearly constrained constant modulus algorithm

In this method, the constraints are constructed in such a way that the signal of interest is received without distortion regardless of how the algorithm updates the weights [50]. In a sense, the constraints define a signal subspace which ensures that the signal of interest is not nulled along with the interferers. The first step is to define a set of linear constraints on the weight vector **w**. Each constraint is expressed in terms of a constraint vector $\mathbf{c}_k$ and a corresponding scalar constraint value $\mathbf{f}_k$. This can be written in matrix notation as $\mathbf{C}^t\mathbf{w} = \mathbf{f}$, where the matrix **C** contains the $\mathbf{c}_k$ vectors as columns and **f** is the vector of constraint values $\mathbf{f}_k$. The overall problem then is defined as min **w** $1/4\langle(|y|^2 - d)^2\rangle$ subject to $\mathbf{C}^t\mathbf{w} = \mathbf{f}$. The constraint problem can be converted to an unconstraint one through the use of a preprocessor called the generalized sidelobe canceller. This structure essentially decomposes the adaptive weight vector **w** into constrained and unconstrained components. Figure 3.4 shows the weight vector decomposition of the generalized sidelobe canceller. From this figure the overall weight vector can be written as $w = w_q - W_s w_a$ where $\mathbf{w}_q$ is the upper quiescent vector and $\mathbf{W}_s$ is the lower path blocking matrix. Both $\mathbf{w}_q$ and $\mathbf{W}_s$ depend upon the constraint equations and are thus fixed, non-adaptive components. $\mathbf{W}_s$ is any matrix which satisfies $\mathbf{C}^t\mathbf{W}_s = 0$. The upper path vector $\mathbf{w}_q$ ensures that the constraint equations are satisfied and is given by $\mathbf{w}_q = \mathbf{C}(\mathbf{C}^t\mathbf{C})^{-1}\mathbf{f}$. The decomposition property can be easily verified. Clearly the adaptive weight vector $\mathbf{w}_a$ is unconstrained and this implies that $\mathbf{w}_a$ can be freely adapted using any criterion. Hence by using the generalized sidelobe canceller structure, the LCCMA problem can be stated as min $\mathbf{w}_a$ 1/4<(|y|2 - d)2> and then the recursion for

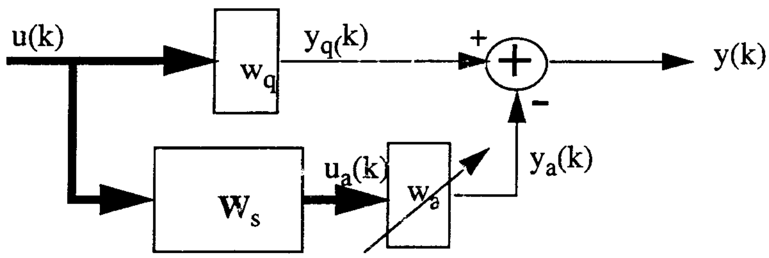


Figure 3.4 The generalized sidelobe canceller

$\mathbf{w}_a$ will be [50]:

$$w_a(n+1) = w_a(n) + \mu(|y(n)|^2 - \delta)y^t(n)u_a(n) \tag{61}$$

The only difference between the update recursion for $\mathbf{w}_a$ in LCCMA and that of $\mathbf{w}$ in CMA is the vector component in the driving term. For the CMA the driving term has the original input vector $\mathbf{u}$(n) while for LCCMA the driving term has the transformed data vector $\mathbf{u}_a$=$\mathbf{W}_s\mathbf{u}$. Though these recursion are very similar to CMA, the LCCM algorithm does not update iteration for $\mathbf{w}_a$ alone but together with the generalized sidelobe canceller.

For DS-CDMA single user detection a proper choice for the linear constraints would be to pass the desired user's signal with unity gain and to null the interfering users. Here, $\mathbf{C} = s_1$, f = 1. So the constraint will be $\mathbf{C}^t\mathbf{w} = 1$; which is equivalent to $\mathbf{w} = \mathbf{s}_1 + \mathbf{w}_a$ and $\mathbf{s}_1\mathbf{w}_a = 0$. Now the constraint portion of the weight vector is $\mathbf{w}_q = \mathbf{s}_1$. The lower blocking matrix $\mathbf{W}$ is chosen to be $\mathbf{W} = [\ \mathbf{e}_1\ \mathbf{e}_2\ ....\ \mathbf{e}_{L-1}]$; where $\mathbf{e}_l$ is the l^{th} eigen vector corresponding to the zero eigen values of matrix $\mathbf{A}$ of dimension L x L and given by, $\mathbf{A} = [\ \mathbf{s}^t_1\ \mathbf{0}\ \mathbf{0}\ ...\ \mathbf{0}]^t$. Then the LCCM algorithm is given by [50],

$$\mathbf{w}_a(0)= [\,0 \;\; 0 \,.....\, 0] \tag{62}$$

$$\mathbf{w}(m) = \mathbf{s}_1 - \mathbf{W}\mathbf{w}_a(m) \tag{63}$$

$$y_1(m) = \mathbf{w}^t u(m) \tag{64}$$

$$\mathbf{u}_a(m) = \mathbf{W}\, \mathbf{u}(m) \tag{65}$$

and the update of $\mathbf{w}_a$ is given by Eq. *61*.

The requirements of the LCCMA to work are: 1) the knowledge of the chip sequence for the desired user must be known and 2) it requires the timing of the desired user.

The simulation is carried out using the LCCMA adaptive method for asynchronous DS-CDMA system with 30 users present in the system. The Gold code of length 63 is used for spreading the data bits for each user. The Figure 3.5 shows the convergence in error e(n) with increase in number of bit iteration.

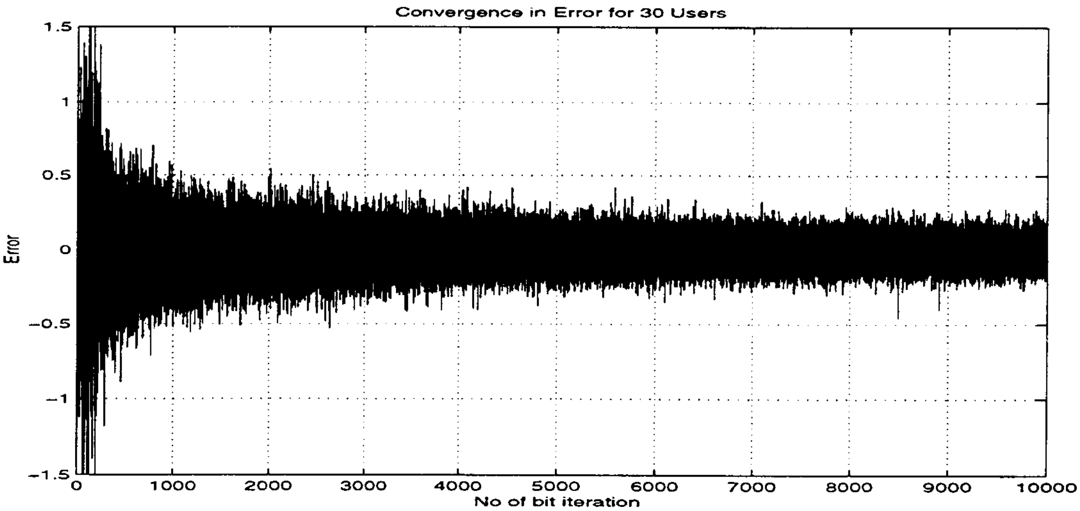


Figure 3.5 Convergence on error term using the LCCMA adaptation with 30 users present in the system.

3.5 Comparison of adaptive methods

The least mean-squared (LMS) algorithm is the simplest and is having the least complexity from the hardware point of view. But the rate of convergence for the LMS adaptation is very slow. The LMS algorithm does not pose any bound of the number of users that can be present in the system. Although for convergence, as the user number changes, the critical step size of the algorithm has to change to maintain stability of the system. As the number of users becomes large, in addition to the minimum mean-squared error (J_{min}), the error will have an excess average mean-squared error. Thus the near-far property of the LMS adaptation for DS-CDMA loses the ground for large number of users present in the system, which is a must for higher capacity. The second problem is that, if the step size is maintained same as for steady state condition for some number of users, under Rayleigh fading, the LMS algorithm may show instability. The normalized least mean squared (NLMS) algorithm shows a better way of handling the Rayleigh fading situation. Under Rayleigh fading the NLMS algorithm will try to follow the minimum point of the convex bowl of the error surface, but as it changes constantly, it never converges to the steady state value. Thus the overall receiver will lose the bit error rate performance.

The recursive least square algorithm has the best advantage of very fast convergence as well as convergence under nonstationary environment like Rayleigh Fading. But RLS algorithm is hardware intensive. Also, the convergence of RLS under Rayleigh fading will not be same as under steady state condition. So it will have same BER performance loss as the LMS adaptation. The RLS algorithm can be applied in synchronous and asynchronous DS-CDMA. But it should be noted that when applied in asynchronous system, the weighting factor has to be small for time varying system which may cause instability because **R**(n) tends to be ill-conditioned [52]. This happens especially if the noise is low and number of users approaches L/2, where L is number of chip in a bit time period (the processing gain) [52].

The linearly constrained constant modulus algorithm is the most promising as it can work in multi-user and Rayleigh fading condition still providing the steady state performance under blind adaptation. Till now it has been applied to the synchronous DS-CDMA system. It also has been simulated for asynchronous CDMA system in this thesis. But it is hardware intensive as it requires eigen values and eigen vector calculation of matrix **A** to find the matrix **W**. Moreover it has the capture problem and as the adaptation process is a nonlinear one, it has local minima.

All the above mentioned adaptive processes have mean squared convergence error in presence of large number of users in the system as shown in the simulations specially for the LMS and LCCMA adaptation. This reduces the near-far immunity of the DS-CDMA receiver. This is more prominent in DS-CDMA asynchronous channel, as it is dimension limited more than the synchronous system. In the next chapter, the decision feedback cancellation structure will be discussed which helps the adaptive processes to regain the lost near-far immunity even in presence of large number of users.

Chapter 4. Near-far resistant multiuser adaptive system

In this chapter an asynchronous channel for DS-CDMA is considered and gradually the multi-user access interference (MAI) problem is solved at base station using adaptive method. According to the explanation given in chapter 3, for further theoretical study, the least mean square (LMS) algorithm is considered as the adaptive method to get the tap coefficients $\mathbf{w}_k$. At first the channel model will be restated for the asynchronous DS-CDMA transmission. The LMS adaptation for DS-CDMA asynchronous channel was first considered on the received signal in [31] where its steady state solution was also mentioned. It was shown in chapter 3 that under fast Rayleigh fading condition-the adaptation process will fail to converge for the same step size as it was considered for system without Rayleigh fading. To prevent this one may consider Normalized LMS adaptive method. In the proposed method this has been avoided by generating a signal from the knowledge of all users' spreading sequence and their delays in bit arrival time. Also in the proposed method, application of decision feedback cancellation scheme circumvents the problem of near-far resistance due to the mean-square error and convergence error in adaptive process. Finally, the theoretical bit error rate has been found out under additive white Gaussian noise condition with and without Rayleigh fading present in the system.

4.1 Channel Model

The baseband received signal for the asynchronous AWGN channel with multipath Rayleigh fading is formulated as,

$$r(t) = \sum_{n=-N}^{N} \sum_{k=1}^{K} a_k b_k(n) s_k(t - nT_b - \tau_k) + \sigma u(t) \tag{66}$$

where, r(t) is the received signal, a_k is the k^{th} user amplitude (in presence of fading, it is time varying complex number), $b_k(n)$ is the n^{th} bit of the k^{th} user and $s_k(t)$ is the k^{th} user's spreading chip waveform. T_b and T_c are bit and chip duration, respectively. The channel noise u(t) is modeled as normalized AWGN with variance σ^2. The delay τ_k can be written as $\tau_k = l_k T_c$, where l_k is an integer. In the asynchronous channel model, it is assumed that the k^{th} user is shifted by one chip duration T_c successively from the previous user. Also, it is assumed that the length of complete chip sequence is L, chip value is limited to +/-1 and bit duration $T_b = LT_c$.

Adaptive receivers, as mentioned in [36]- [38], work directly over the received signal $\mathbf{r}[n] = [r_1(n)\ r_2(n) ....r_L(n)]$; $r_i(n) = i^{th}$ bit of $\mathbf{r}[n]$ sampled at chip rate. As shown in Figure 4.1, the received signal at the base station consists of all transmitted users $\{a_1 b_1, a_2 b_2, ..., a_K b_K\}$ coded by signature code ($\mathbf{s}_k$) and received after delay of τ_1, $\tau_2 ...$, τ_K. The base station has the knowledge of code $\mathbf{s}_k$ and by synchronization it determines τ_k. The base station adaptively decodes the received signal by the sequence $\{\mathbf{w}_1$,

$w_2,....,w_K\}$. To obtain $b_k(n)$, the conventional method adaptively generates a sequence w_k for the k^{th} user, such that the sign (sgn) of the inner product of w_k and $r[n]$ estimates the transmitted bit of the desired user:

$$\hat{b}_k(n) = \operatorname{sgn}\left(w_k r^t[n]\right) \tag{67}$$

where, $r^t[n]$ signifies transpose of the vector $r[n]$. These method do not consider the case when the received signal is corrupted by fading (abrupt signal attenuation) where due to fading the adaptation process converges slowly or does not converges at all.

4.2 The Proposed Adaptive Receiver

To have the same convergence rate under fading condition, in the proposed method, the adaptation (as shown in Figure 4.2) is operated on a generated signal $r'(n)$. So, the attractive property of locking onto the signal is lost, which is self adaptation

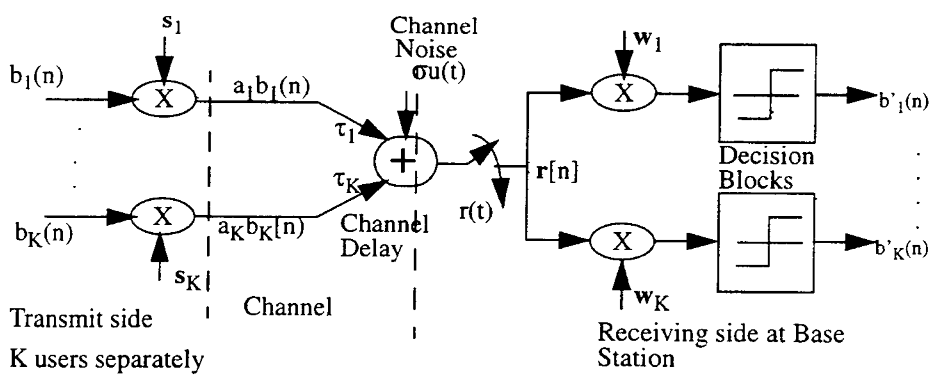


Figure 4.1 Model of transmitter and receiver structure for DS-CDMA

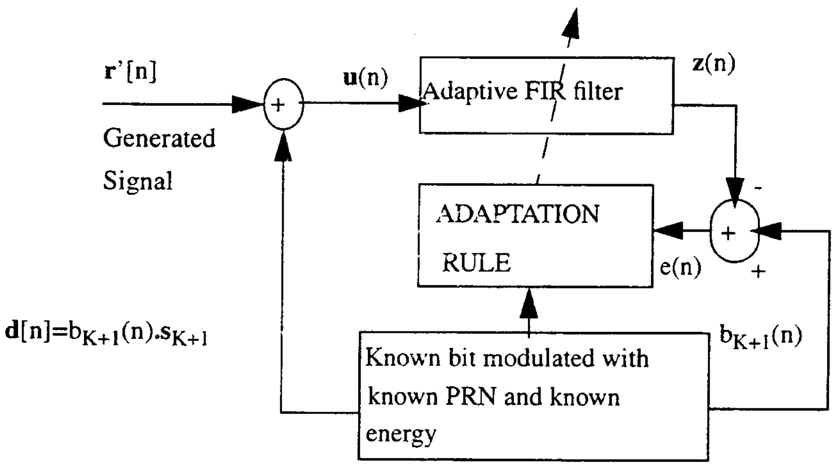


Figure 4.2 Least Mean Square Adaptive method

without knowing the time delay (τ_k) from the adapted coefficients [31]. But the proposed generated signal (along with training sequence) allows the adaptation to be independent of the channel. Here, the received signal is generated knowing the existing users' chip sequence and their time delays as shown in Figure 4.3. Also it is assumed that once new users start communicating, their chip sequences and their time delays are known (this part will be covered separately in chapter 5 on synchronization) at the base station. Figure 4.3 shows the proposed structure, which avoids higher bit error rate due to J_{min} and convergence error using the decision feedback cancellation similar to the parallel interference cancellation scheme where the LMS adaptation is used on the generated signal.

A method for estimating the amplitude of the signal $a_k b_k$ is shown in Figure 4.4. A similar approach is outlined by Moshavi and is known as parallel interference cancellation [7]. Given the adaptive coefficients w_k, the first set of amplitude α^1_k for k^{th} user (here superscript 1 denotes the first iteration) are estimated and are used subsequently to estimate the received signal **r**[n]. This estimate of the received signal is called $\zeta^1[n]$, generated using the amplitude estimate $\alpha^1{}_k$ and the signature code (s_k) for each user. The error signal $\varepsilon^1[n] = \mathbf{r}[n] - \zeta^1[n]$ is fed to the second stage of decision feedback cancellation.

The approximate amplitude $\alpha^1{}_k$ for the k^{th} user is formed by:

$$\alpha_k^1[n] = \left(w_k r^t[n]\right) \tag{68}$$

The error signal,

$$\varepsilon^1[n] = r[n] - \sum_{k=1}^{K+1} \alpha_k^1 s_k \tag{69}$$

This process is repeated where $\varepsilon^1[n]$ is the input to the decision feedback of the second stage. The error for the estimate of amplitude is $\delta_k = a_k b_k - \alpha^1{}_k$. The error $\varepsilon^1[n]$ is (τ_k is not shown for simplicity):

$$\varepsilon^1[n] = \sum_{k=1}^{K} \delta_k s_k \tag{70}$$

Let $\delta = \sup\{\mathrm{abs}(\delta_k)\}$ (sup = supremum), we can rewrite (26) as:

$$\varepsilon^1[n] \le \delta y[n] \tag{71}$$

If the adaptation is converging, then $0<\delta<1$. If the decision feedback cancellation procedure is repeated for m stages,

$$\varepsilon^m[n] \le \delta^m y[n] \tag{72}$$

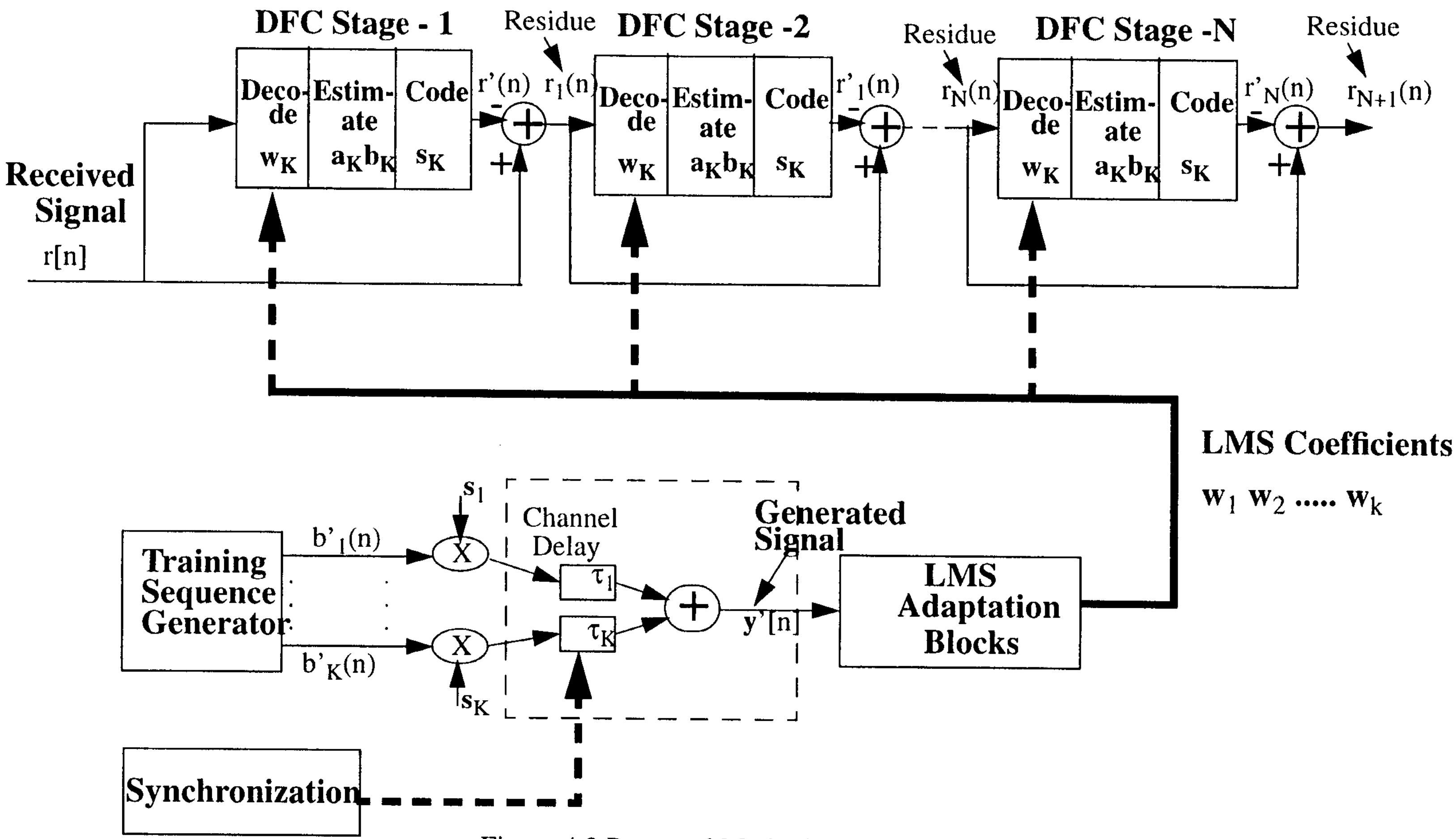


Figure 4.3 Proposed Method

As m becomes large, the residue term $\varepsilon^m[n]$ will tend to zero since δ^m goes to zero.

In the presence of noise, the noise energy (variance $\sigma^2(\varepsilon^1[n])$) at the output $\varepsilon^1[n]$ is:

$$\sigma^2(\varepsilon^1[n]) = \left(1 + x_1^{\,2} + \ldots + x_{K+1}^{\,2}\right)\sigma^2 \tag{73}$$

where,

$$x_k^2 = w_k w_k^t \tag{74}$$

Hence, the noise energy at the output $(\sigma^2(\varepsilon^1[n]))$ is the addition of noise variance for all users multiplied by the coefficients $w_k w^t{}_k$. The details of noise magnification through number of decision feedback cancellation stages are discussed later in this chapter.

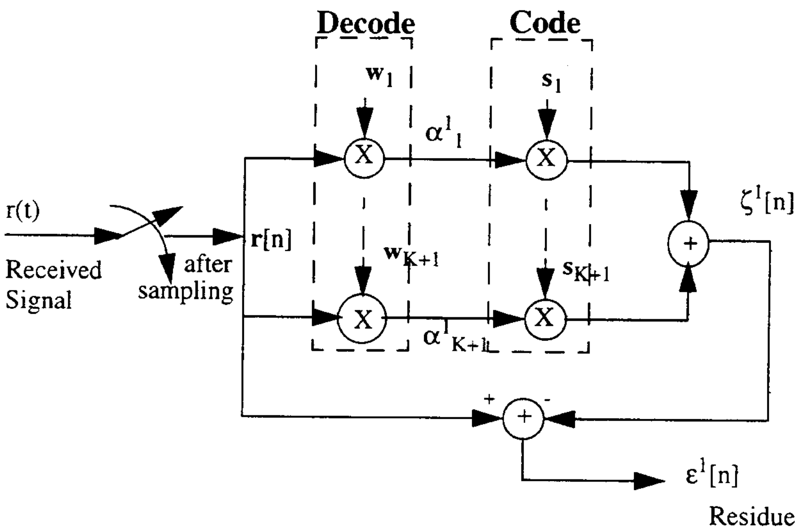


Figure 4.4 Single stage of Decision Feedback for Amplitude estimation

4.3 Bit error rate in the Proposed Method

In the last section a method of decision feedback cancellation (DFC) is proposed for $\mathbf{w}_k$ which partially decorrelates the user from multiple access interference (MAI). This method is similar to Parallel Interference Cancellation (PIC) method. In this section the bit error rate is calculated under additive white Gaussian noise condition for individual user in DS-CDMA asynchronous channel when demodulated using the proposed demodulator. It is not possible to determine the exact BER theoretically. Instead the upper bound of the BER is found out. The received signal Figure 66 is repeated here for convenience,

$$r(t) = \sum_{n=-N}^{N} \sum_{k=1}^{K} a_{k,n} b_{k,n}(n) s_k(t - nT - \tau_k) + \sigma u(t) \tag{75}$$

where, $a_k = 1$ and $\tau_k = (k-1)T_c$. Now, in the first stage of DFC, for k^{th} user the amplitude will be,

$$\alpha_n^{1,k} = r \bullet w_k^t = b_{k,n} + \delta_{k,n} + z_{k,n} \tag{76}$$

where k stands for k^{th} user, n stands for n^{th} transmitted bit, b stands for bit, δ (<1) stands for MAI present in the demodulated signal and z is the demodulated noise part. The $\mathbf{w}_k$ are the partially decorrelating coefficients found from the LMS adaptation. Now the residue ε^1 formed after stage one can be given as:

$$\varepsilon_n^1 = y - \sum_{k=1}^{K} (b_{k,n} + \delta_{k,n} + z_{k,n}) \bullet s_k(t-(k-1)T_c) = \sum_{k=1}^{K} -(\delta_{k,n} + z_{k,n}) s_k(t-(k-1)T_c) + \sigma^2 u(t) \tag{77}$$

At this point it is observed that $\delta_{k,n}$ is not same for varying k and n. Similarly, $z_{k,n}$ is also not a constant. Hence, let us assume that δ_n = supremum of $\{\delta_{1,n} \ldots \delta_{K,n}\}$ and z_n = supremum of $(z_{1,n} \ldots z_{K,n}\}$. Normally the noise term $z_{k,n} = (\mathbf{w}_k . \mathbf{w}^t_k)\sigma^2 u(t)$. Thus the ε^1 has a noise variance that can be written as

$$var(\varepsilon^1) = \sigma^2\left(1 + \sum_{k=1}^{K} w_k w_k^t\right) \tag{78}$$

which is same as Eq. *73*. Now replacing $\delta_{k,n}$ and $z_{k,n}$ by δ_n and z_n respectively in Eq. *77*,

$$\varepsilon_n^1 = \sum_{k=1}^{K} -(\delta_n + z_n) s_k(t-(k-1)T_c) + \sigma^2 u(t) \tag{79}$$

Now, in the second stage of DFC the amplitude estimate for k^{th} user will be,

$$\alpha_n^{2,k} = -(\delta_{k,n} + z_{k,n}) - \delta_n(\delta_{k,n} + z_{k,n}) + z_{k,n} \tag{80}$$

and the residue term $\varepsilon^2{}_n$ after second stage of DFC will be,

$$\varepsilon_n^2 = \sum_{k=1}^{K} (\delta_n(\delta_n + z_n) - z_n) s_k(t-(k-1)T_c) + \sigma^2 u(t) \tag{81}$$

In the third stage of DFC cancellation, the amplitude estimate for k^{th} user will be:

$$\alpha_n^{3,k} = \left(\delta_n^2 + \delta_n z_n - z_n\right) + \delta_n\left(\delta_n^2 + \delta_n z_n - z_n\right) + z_{k,n} \tag{82}$$

and the residue term $\varepsilon^3{}_n$ after third stage will be:

$$\varepsilon_n^3 = \sum_{k=1}^{K} \left[\delta_n\left(\delta_n^2 + \delta_n z_n - z_n\right) + z_n\right] s_k(t-(k-1)T_c) + \sigma^2 u(t) \tag{83}$$

For q number of DFC stages, the amplitude estimation of k^{th} user and the residue after q^{th} stage can be given as:

$$\alpha^{q,k} = (-1)^{q-1}[\chi + \delta_n \chi] + z_n \tag{84}$$

$$\varepsilon_n^q = \sum_{k=1}^{K} -\left[(-1)^{q-1}(\delta_n \chi) + z_n\right] s_k(t-(k-1)T_c) + \sigma^2 u(t) \tag{85}$$

where,

$$\chi = \delta_n^{q-1} + \left[\delta_n^{q-2} - \delta_n^{q-3} + \delta_n^{q-4} - \ldots - 1\right] z_n \tag{86}$$

The first term in χ represents the MAI present and the rest represents the magnified noise term. Adding all the estimated amplitudes of q stages,

$$\alpha_n^k = b_{k,n} + \left[(-1)^{q-1}(\delta_n \chi) + z_n\right] \tag{87}$$

So the variance of the noise term in estimated amplitude,

$$var\left(\alpha_n^k\right) = \left[1 + \delta_n^2 + \delta_n^4 + \ldots + \delta_n^{2(q-1)}\right] z_n \sigma^2 + \delta_n^{2q} \tag{88}$$

Thus the probability of error can be given as

$$P_e = Q\left(\sqrt{\frac{1}{var\left(\alpha_n^k\right)}}\right) \qquad (89)$$

where, Q(x) is given in the Eq. *48*. This is the upper bound of bit error rate.

Similarly, under Rayleigh Fading condition one can represent the received signal by $r(t)= \alpha(t) \exp(-j\theta(t))s(t)+n(t)$ where s(t) is the transmitted signal, $\alpha(t)$ is the gain of the channel, $\theta(t)$ is the phase of the channel and n(t) is the additive white Gaussian noise. Then, the bit error rate can be given as [1],

$$P_e = \frac{1}{2}\left[1 - \sqrt{\frac{\Gamma}{1+\Gamma}}\right] \qquad (90)$$

where,

$$\Gamma = \frac{E_b}{N_0}\alpha^2 = \left(\sqrt{\frac{1}{var\left(\alpha_n^k\right)}}\right)\alpha^2 \qquad (91)$$

4.4 Noise Propagation through DFC stages

It is mentioned in Eq. *73*, section 4.2 that received noise will be magnified in each stage. First only a single stage is considered with only Gaussian noise as the received signal for synchronous DS-CDMA case. Here it is considered that the adaptation process is converged to $\mathbf{w}_k$ tap coefficients for the k^{th} user in the synchronous case. The Gaussian noise source produces N data points for one bit interval in absence of any transmitted bit from all the users. The amplitude estimate for k^{th} user in the first stage of DFC scheme will be $\alpha^{1,k} = Nw_k^t$. If the Gaussian source is having a variance of σ^2, then $\alpha^{1,k}$ will have a variance of $\sigma^2_{1,k}=(\mathbf{w}_k\mathbf{w}^t_k\sigma^2)$. Now in respreading, $\alpha^{1,k}$ will be used to multiply the spreading code $\mathbf{s}_k$ and the respreaded sequence for all the users will be added to form ζ^1, the estimate of the received signal. Here the k^{th} respreaded sequence will constitute a random sequence with $+/-\alpha^{1,k}$ coefficient which will be similar to a binomial random variable. The addition of spreaded sequence for all K users will produce a random sequence with almost Gaussian distribution with a variance as shown in Eq. *73*. Now the effect of all the stages together is explored. To make the computation simpler, it is considered that the error in the convergence in the adaptation process, δ_n = supremum of $\{\delta_{1,n}.....\delta_{K,n}\}$ and α^n = supremum of $\{\alpha^{1,n}.....\alpha^{K,n}\}$. Now the residue at the end of the first stage will be

$$\varepsilon^1 = \left(N - \sum_{k=1}^{K} \alpha^{1,n} s_k\right) = \left(N - \alpha^1 \sum_{k=1}^{K} s_k\right) \tag{92}$$

The amplitude estimate in the second stage will be

$$\alpha^{2,k} = \left(N - \sum_{k=1}^{K} \alpha^{1,n} s_k\right) s_k = \left(N - \alpha^1 \sum_{k=1}^{K} s_k\right) s_k = \alpha^1 - \alpha^1(1+\delta_1) = -\alpha^1\delta_1 \tag{93}$$

So, the residue at the end of second stage will be,

$$\varepsilon^2 = \left(N - \alpha^1 \sum_{k=1}^{K} s_k + \alpha^1\delta_1 \sum_{k=1}^{K} s_k\right) \tag{94}$$

Similarly, the residue at the end of third stage will be,

$$\varepsilon^3 = \left(N - \alpha^1 \sum_{k=1}^{K} s_k + \alpha^1\delta_1 \sum_{k=1}^{K} s - \alpha^1\delta_1^2 \sum_{k=1}^{K} s_k\right) \tag{95}$$

At the end of q stages, the residue will be for noise only case,

$$\varepsilon^q = \left(N + \sum_{i=1}^{q}\left((-1)^q \alpha^1 \delta_1^{q-1} \sum_{k=1}^{K} s_k\right)\right) \tag{96}$$

Thus, one can observe that the noise term does not get magnified beyond a point with increase in the number of DFC stages. This is valid even for asynchronous DS-CDMA demodulation.

One can also think one stage of the Decision Feedback Cancellation Stage as a matrix multiplier followed by subtraction from the received signal itself. So, if the received signal is **r**[n] (sampled version), the output of the inner product for one user $\mathbf{r}[n]\mathbf{w}_k^t$ and the respreaded signal will be $\mathbf{r}[n]\mathbf{w}_k^t\mathbf{s}_k$. Here $\mathbf{w}_k^t\mathbf{s}_k$ is a matrix. So the decision feed back cancellation is a linear process and as whole works as a linear filter. The condition of stable operation of the filter is that the error bound of the convergence in adaptation (δ) is less than 1. As long as the filter is stable, the noise will not increase beyond a limit or in a sense its statistics will remain almost constant.

Chapter 5. Synchronization

In this chapter a theory has been developed which will help to synchronize any new user entering the system. Synchronization is the basic requirement in communication and it has to be done even before the demodulation of the transmitted bits start. Synchronization in digital communication can be divided into three main parts: frequency synchronization, phase synchronization and timing or bit synchronization. Here the timing or bit synchronization aspect is only considered.

Before discussing the theoretical aspect, it would be better to mention that most of the synchronization works for multiuser DS-CDMA attempt to recover bit timing under the assumption that the pseudo-random sequences used for spreading the transmitted bits are long. These works mainly try to solve the problems in application of IS-95. Recently, it has been shown that linear decorrelating detectors along with adaptive decorrelating detectors are promising in respect to increase in cell capacity and better multiple-access interference cancellation which in turn allows more flexible power control. Some of the recent works deal with short pseudo-random codes which are most suitable for adaptive and linear decorrelating detectors. In the previous chapter, a novel method of decision feedback cancellation using coefficients from least mean square adaptation is used to get back near-far resistance of adaptive method in presence of a large number of users. But this large capacity cannot be achieved if a new user cannot be synchronized. Here, after preliminary discussion of other synchronization procedures, the importance of usage of the same decision feedback cancellation scheme is stressed where it is assumed that a new user arrives in the system when existing users are already using decision feedback cancellation scheme. The simulation results will be presented in chapter 6 supporting the theory developed in this chapter.

The basic theory behind all the methods stated in the following sections is to cancel the cross-correlation component of existing users in the received signal so that a clean signal is found out with the new user's received signal. This clean signal is correlated with the known pseudo random sequence of the new user to find the bit timing. Success of a procedure depends on how much clean signal it can produce.

5.1 Synchronization using Blind Adaptation

In case of the linear decorrelating detector, it is known that one can cancel the multiple-access interference term completely. In that situation, the coefficients is found out by inverting the correlations matrix and used in decorrelating the matched filter output. In the adaptive decorrelating detector, the tap coefficients of adaptive FIR filters are found, and used in the matched filter instead of the PN sequences. But applying least mean square adaptation on the received signal means training sequence will be required for the new user as well as all the existing users, though it can solve the problem of bit synchronization for the new user.

Instead of using LMS adaptation involving training sequences, it is also possible to have blind LMS adaptation on the received signal, although it converges slower than LMS adaptation. The blind adaptation is also affected by channel fading, which is also true for LMS adaptation with training sequence transmitted from the mobile user. The details of blind adaptation is given in chapter 2..

If the blind adaptation converges in the presence of a new user then one can use it's coefficients and demodulate all the existing users correctly with the correct estimation of their amplitudes. These estimated amplitudes can be re-spreaded using the PN sequence for each existing user and cancelled from the received signal to form a clean signal with the new user and noise only. Then by correlating the clean signal with the PN sequence of the new user we can find the bit timing of the new user. This will be possible only if the blind adaptation converges to zero.

In reality the blind adaptation in the presence of channel noise and fading will not converge to zero. Then one can use the decision feedback cancellation scheme along with the converged tap coefficients of blind adaptation which will again produce a clean signal. But this procedure will be time consuming as the LMS blind adaptation converges slowly. The recursive least square adaptive method can be used to increase the convergence rate at the expense of computational complexity. But it will still take considerable amount of time. Figure 5.1 shows the decision feedback scheme along with blind adaptation for synchronization. The problem of this method is that the blind adaptation as it works on the received signal will be affected by fading. In the next section a method is described which does not get affected by fading.

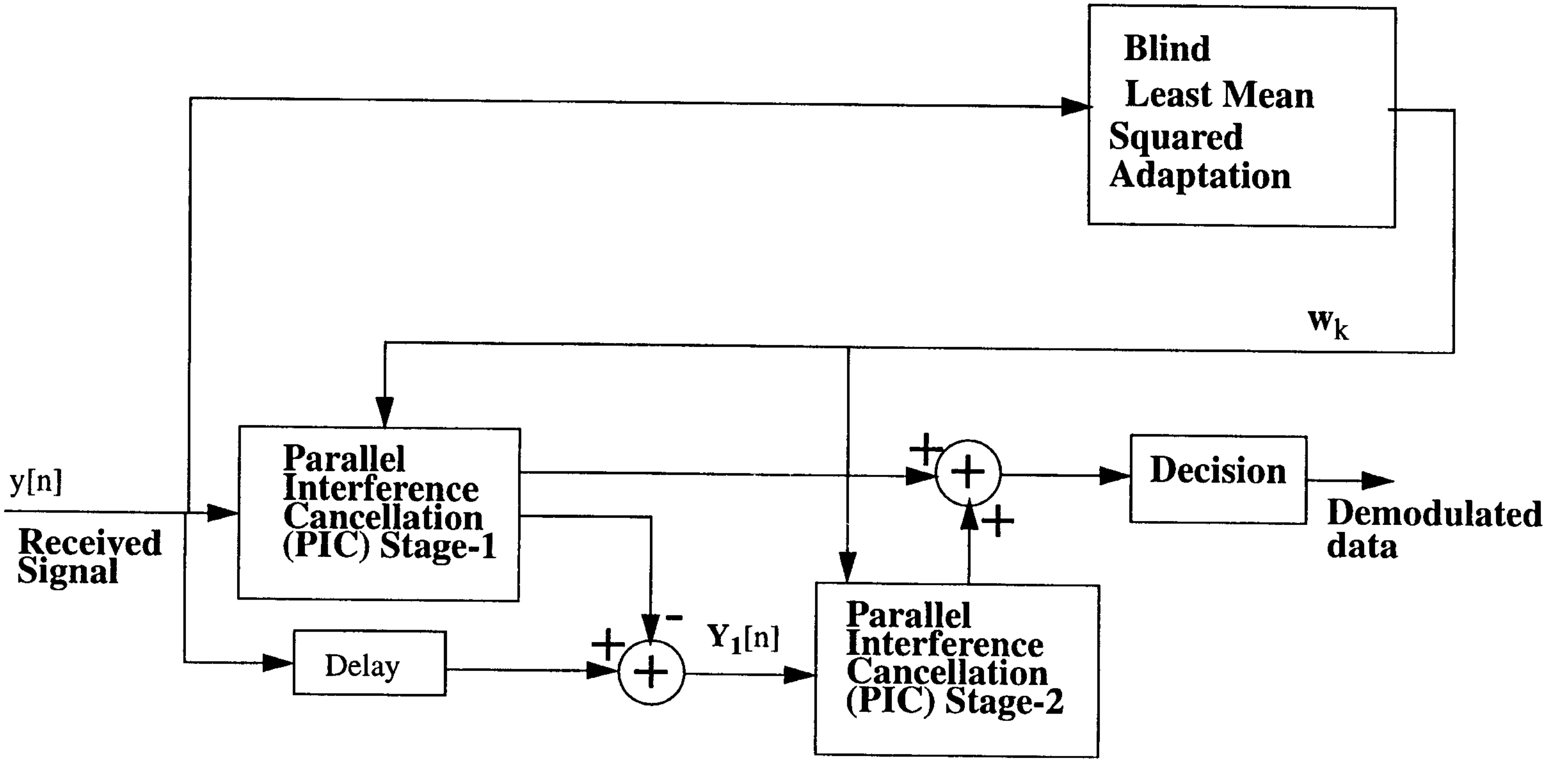


Figure 5.1 Proposed Method for synchronization using blind adaptation

5.2 Synchronization using averaging

It is observed that the convergence of the blind adaptation is difficult in presence of fading and it is also a slow process. In the following method, the usage of the blind adaptation is circumvented using a training sequence only required for the new user(s). As it does not depend on adaptation on the received signal, its process of synchronization will not be hampered by channel fading though it will increase the acquisition time.

The concept of this process takes advantage of the fact that short PN sequences are used for adaptation. This process starts if the residue from the decision feedback cancellation scheme increases beyond a certain limit. In this procedure, the new users will send a constant bit signal modulated by their own PN sequence. Preferably, this PN sequence length is equivalent to a bit time period. At the receiving end in the base station, the received signal is passed through a filter with the same PN coefficients of the new user and the output is averaged over a bit time period. Because, all the existing users are sending random data bits, the crosscorrelation which is fixed depending on the PN sequences of all other users and their time delay will be fixed but changing with the sign of transmitted bit. The autocorrelation for the desired user will be a constant number as the transmitted bit for new user is kept constant. As the number of bits averaged increases, the component due to crosscorrelation will diminish in compare to the autocorrelation which is getting added. Soon the autocorrelation of the PN sequence will be dominant and the bit timing will be clear. The mathematics of the averaging process is shown below. Here, $\mathbf{r}[n]$ is the sampled received signal r(t). Then in presence of K existing users and I new users, the received signal will be,

$$r(t) = \sum_{k=1}^{K} a_k b_k(n) s_k(t - nT_b - \tau_k) + \sigma^2 u(t) + \sum_{i=1}^{I} a_i b_i(n) s_i(t - nT_b - \tau_i) \qquad (97)$$

where, τ_i for i=1,..,I are unknown and b_i for i=1,..,I are constants. For I=1, the average of the matched filter output is taken for the new user over N bit periods. The averaged term will be,

$$r_{mfavg} = \sum_{n=1}^{N} \sum_{k=1}^{K} a_{k,n} b_{k,n}(n) s_k(t - nT_b - \tau_k) + \sum_{n=1}^{N} \sigma u(t) + N a_i s_i(t - nT_b - \tau_i) \qquad (98)$$

where the first term is the average of MAI and as $b_{k,n}$ is random, this average will reduce as N increases. The second term is the noise and the third term is the autocorrelation which increases with N.

The acquisition time will be dependent on three factors: the number of existing users, the time delay and the property of the transmitted bits for the existing users. The term property means the probability distribution of the transmitted bits.

5.3 Synchronization using DFC scheme

In this method, it is assumed that for the existing users adaptation is complete and tap coefficients of the FIR filter converged to $\mathbf{w}_k$ for the k^{th} user for k=1,...,K. Now these $\mathbf{w}_k$ are used in a number of decision feedback cancellation stages. In the absence of any new user, the residue of the last stage will be zero in the absence of noise and in the presence of noise, the residue will be the noise. If any particular user's PN sequence is correlated with this residue, it will show a negligible value. In presence of a new user, the residue will have the received new user along with the noise term, as well as the crosscorrelation terms between new user and old existing users. This can be correlated with the PN sequence of the new user and the peak in the correlation will point out the time delay.

For understanding purposes a case is considered with two existing users. Now, synchronization for a new user is tried in presence of existing two users whose τ_k are already known. For the two existing users, the $\mathbf{w}_1$ and $\mathbf{w}_2$ are also already known which partially decorrelates the desired signal from MAI. In absence of a new user, let the received signal be $\mathbf{r}[n]$, then the amplitude estimations in the first stage of PIC will be,

$$E_{1,1} = \mathbf{r}[n]\, \mathbf{w}^t{}_1 = a_1 b_1 + \delta_1 + z_{1,1} \qquad (99)$$

and

$$E_{1,2} = \mathbf{r}[n]\, \mathbf{w}^t{}_2 = a_2 b_2 + \delta_2 + z_{1,2} \qquad (100)$$

where δ_1 and δ_2 are the MAI terms and $z_{1,1}$ and $z_{1,2}$ are the noise terms. In presence of the single new user the received signal will be $\mathbf{r}[n]$ + $a_3 b_3\, s_3(t\text{-}\tau_3\text{-}nT_b)$ and then the amplitude estimations for existing two users in the first stage of PIC will be

$$E'_{1,1} = \mathbf{r}[n]\, \mathbf{w}^t{}_1 = a_1 b_1 + \delta_1 + e_1 + z_{1,1} \qquad (101)$$

and

$$E'_{1,2} = \mathbf{r}[n]\, \mathbf{w}^t{}_2 = a_2b_2 + \delta_2 + e_2 + z_{1,2} \tag{102}$$

where e_k stands for the interference due to the presence of the new user and all other symbols carry the same meaning as explained earlier. Now if the amplitude estimations are respreaded using their spreading codes and cancel them from the received signal, then the residue $\varepsilon^1[n]$ will be,

$$\varepsilon^1[n] = a_3b_3\, s_3(t\text{-}\tau_3\text{-}nT_b) + \sigma^2u[n] - (\delta_1 + e_1 + z_{1,1})s_1 -(\delta_2 + e_2 + z_{1,2})s_2, \tag{103}$$

Now in the second stage of PIC, the amplitude estimation will be,

$$E'_{2,1} = \varepsilon^1[n]\, \mathbf{w}^t{}_1 = -(\delta_1 + e_1 + z_{1,1}) - \delta_1(\delta_2 + e_2 + z_{1,2}) + e_1 + z_{1,1} \tag{104}$$

and

$$E'_{2,2} = \varepsilon[n]\, \mathbf{w}^t{}_2 = -(\delta_2 + e_2 + z_{1,2}) - \delta_2(\delta_1 + e_1 + z_{1,1}) + e_2 + z_{1,2} \tag{105}$$

Now if δ is the supremum of δ_1, δ_1, e_1 and e_2 then,

$$\varepsilon^2[n] = a_3b_3\ s_3(t\text{-}\tau_3\text{-}nT_b) + \sigma^2u[n] + (\delta(2\delta + z_{1,2})\text{-}(\delta + z_{1,1}))s_1 + (\delta(2\delta + z_{1,1}) - (\delta + z_{1,2})s_2, \tag{106}$$

Comparing (103) and (106), we find that the residue $\varepsilon^1[n]>\varepsilon^2[n]$ as $\delta < 1$ and this process will continue if more number of stages are added. If δ is small, then from $\varepsilon^2[n]$ one can find the timing of delay for the new user by the correlation method.

The above mentioned case can be generalized for existing K users. For generalization the number of new users are considered as I. This received signal will pass through number of decision feedback cancellation stages with known w_k for existing K users. In presence of new users, the received signal can be rewritten as

$$r(t) = \sum_{k=1}^{K} a_k b_k(n) s_k(t - nT_b - \tau_k) + \sigma^2 u(t) + \sum_{i=1}^{I} a_i b_i(n) s_i(t - nT_b - \tau_i) \tag{107}$$

The amplitude estimate in first stage of DFC for existing K users can be given as,

$$\alpha^1_{k,n} = a_k b_k + \delta_{k,n} + e_{k,n} + z_{k,n} \tag{108}$$

The superscript 1 signifies the first stage and in the subscript k stands for k^{th} user and n stands for the n^{th} transmitted bit. The second term $\delta_{k,n}$ stands for the convergence error due to the crosscorrelation with the exiting users, $e_{k,n}$ stands for the error due to the crosscorrelation with the new users and $z_{k,n}$ stands for the noise term. For future calculations, the subscript k is removed and δ_n = supremum ($d_{k,n}$ for k=1,...,K), e_n = supremum ($e_{k,n}$ for k=1,...,K) and z_n = supremum ($z_{k,n}$ for k=1,...,K) are considered. So, (108) takes the form of

$$\alpha^1_n = a_k b_k + \delta_n + e_n + z_n \tag{109}$$

Similarly, one can form the residue of the first stage as,

$$\varepsilon^1_n = -\sum_{k=1}^{K} (\delta_n + e_n + z_n) s_k(t - nT_b - \tau_k) + \sigma^2 u(t) + \sum_{i=1}^{I} a_i b_i(n) s_i(t - nT_b - \tau_i) \tag{110}$$

In the second stage of decision feedback cancellation, the amplitude estimate will be,

$$\alpha_n^2 = -\delta_n - \delta_n(\delta_n + e_n + z_n) \tag{111}$$

and the residue will be,

$$\varepsilon_n^2 = \sum_{k=1}^{K} [\delta_n(\delta_n + e_n + z_n) - (e_n + z_n)] s_k(t - nT_b - \tau_k) + \sigma^2 u(t) + \sum_{i=1}^{I} a_i b_i(n) s_i(t - nT_b - \tau_i) \tag{112}$$

If one considers q number of decision feedback stages (where, q>1), then the amplitude estimate at the q^{th} stage will be,

$$\alpha_n^q = (-1)^{q-1}[\chi + \delta_n \chi] + (e_n + z_n) \tag{113}$$

and the residue term after the q^{th} stage will be,

$$\varepsilon_n^q = \sum_{k=1}^{K} -\left[(-1)^{q-1}\delta n\chi + (e_n + z_n)\right] s_k(t - nT_b - \tau_k) + \sigma^2 u(t) + \sum_{i=1}^{I} a_i b_i(n) s_i(t - nT_b - \tau_i) \tag{114}$$

where, χ is given by,

$$\chi = \delta_n^{q-1} + \left[\delta_n^{q-2} - \delta_n^{q-3} + \delta_n^{q-4} - \ldots - 1\right](e_n + z_n) \tag{115}$$

The total amplitude estimate will be,

$$\alpha_k = a_k b_k + e_n + z_n + \delta_n \chi \tag{116}$$

The variance in the noise term will be,

$$var(\alpha_k) = \left[1 + \delta_n^2 + \delta_n^4 + \ldots + \delta_n^{2(q-1)}\right](e_n + z_n)\sigma^2 + \delta_n^{2q} \tag{117}$$

So the probability of error for existing users in presence of new users can be given as

$$P_e = Q\left(\sqrt{\frac{1}{var(\alpha_k)}}\right) \tag{118}$$

In (114) it is observed that the first term is the residue of the existing users due to crosscorrelation with the new users and will be less in magnitude than that in (107). Hence, correlation of (114) and the new users PN sequence will result in faster acquisition of delay time.

This synchronization using DFC stages is motivated by the work done in [46] where instead of DFC, stages of simple parallel interference cancellation structure was considered. Applying DFC with adapted tap coefficients instead of PN sequence in matched filter gives better results as it will be shown in chapter 6.

Chapter 6. Simulation results

In this chapter the simulation results are presented in an attempt to prove the theoretical work done in the previous chapters. The simulations can be divided into three parts. The first part will show that all three adaptive methods (the least mean-squared, the recursive least squared and the linearly constraint constant modulus algorithm), suffer from near-far problem when large number of users are present in the system. In the second part, using the decision feedback cancellation scheme proposed here, the adaptive methods regain the near-far immunity. For this simulation only the least mean square adaptive method will be considered. In the third part the results on synchronization problem will be provided for two cases: using the method of averaging and using the residue of decision feedback cancellation. In the last simulation, a non-coherent QPSK scheme will be proposed. Simulation on this structure is not considered here. But first of all, the asynchronous DS-CDMA system along with the choice of code for spreading sequence will be discussed.

6.1 System model and spreading code

The system will consist of the transmit side where the individual user are transmitting data asynchronously, the channel which introduces the channel noise modeled as additive white Gaussian noise (AWGN) and Rayleigh fading which cause the amplitude of the signal to fade randomly and the receiving side which will have a few stages of decision feedback cancellation scheme using the adapted coefficients from the

LMS adaptation for the demodulation. Figure 2.2 and Figure 4.3 in chapter 4 show the system model.

In the transmit side, the individual users modulate the data bit using the spreading sequence and then it is modulated at carrier frequency. To make the simulation simple and to save time, all simulations are done in baseband. Thus the modulation in carrier frequency is not shown. Hence all of the simulations use a baseband BPSK model for the transmission, the channel and a coherent receiver.

The choice of spreading sequence is very critical. Normally for CDMA the maximal length shift register (MLSR) sequences are considered. These are also called m-sequences. The MLSR sequences have very attractive autocorrelation properties, but for a fixed number of shift registers, their numbers are limited. The crosscorrelation of the two MLSR sequences of same length is not good. Moreover, for an asynchronous channel, it is required to have a large number of spreading sequences with good autocorrelation and crosscorrelation properties. The gold codes have these good properties and normally used for simulation of asynchronous channel in the literature. The gold codes are normally generated from two m-sequences (preferred pair). The method of generating m-sequence and the gold sequence and their properties are discussed in [55]. It should be clear that due to the asynchronous nature of the received signal, the gold codes are required which helps to synchronize individual users. In synchronous channel, each individual can use a shifted version of the same m-sequence. For simulation, the channel is always considered asynchronous in nature.

In the simulation, gold codes of length 63 (=L) are considered and they repeat for every data bit period (T_b=LT_c), where T_c symbolizes the chip period. Thus L is the processing gain. The chip is considered to be a rectangular pulse. But in a real system this will be filtered using a raised-cosine filter to limit the radio frequency (RF) bandwidth. The data rate is considered as 5Kbits per second. Thus the total bandwidth will be limited to 630 KHz keeping a provision of including 1/2 convolution coding to improve the bit error rate under rayleigh time-dispersive fading. If the 1/2 convolution error correcting coding is considered then the data rate will be 10 Kbits per second, thus the bandwidth will be 1.26 MHz, almost similar to the bandwidth considered for IS-95.

For simulation, the asynchronous system is modeled by delaying the reception of the transmitted signal from individual users at the base station receiver at integer multiple of the chip duration T_c. In the real system, this delays will be random.

At the receiving end, the data will be sampled at least at the Nyquist rate, that means, the sampling time period T_s at the receiver to be $T_c/2$ or less. For simulation, T_s is set equal to $T_c/4$. It has been found that if the delays are less than T_c, the dimension of the system increases (that is the new dimension will be T_b/T_s) and the adaptive systems show better convergence results. Not only that, even the linear decorrelating one shot detector will able to increase the capacity maintaining full near far resistance. Due to this reason to model a worse situation in the simulation, the delays are considered to be integer multiple of T_c. At the same time, reducing T_s will make the analog-to-digital circuit more complex and following that digital computation will also increase. This should be kept in mind while deciding the T_s for a real system.

6.2 Simulation of adaptive systems

The adaptive systems considered in simulation are the least mean squared adaptation, the recursive least squared adaptation and the linearly constraint constant modulus algorithm. The last two adaptive methods are considered only to show that even their convergence error become prominent when large number of users are present in the system which gives rise to near-far problem. Following that all simulation with the decision feedback cancellation scheme will use the adapted tap coefficients found using the LMS algorithm.

Here, Figure 6.1, Figure 6.2 and Figure 6.3 show the convergence of error using the least mean square algorithm. In Figure 6.1, the total number of users considered are 30. From the simulation result it is clear that even after 10000 bit of iteration the convergence error is +/-0.15. That means that if one of the user's amplitude drops to +/- 0.15 level as compared to that of all other users, it will result in erroneous bit detection in demodulation. Similarly, the Figure 6.2 and Figure 6.3 show the convergence in error term for 10000 bit iteration considering total number of users 40 and 50 respectively. From Figure 6.3 it becomes clear that if the adapted tap-coefficients are used without decision feedback cancellation scheme, the bit error rate will be very poor. Thus in fact, without decision feedback cancellation, if the adapted tap coefficients are used for demodulation, the receiver at base station will suffer from the near-far problem. This

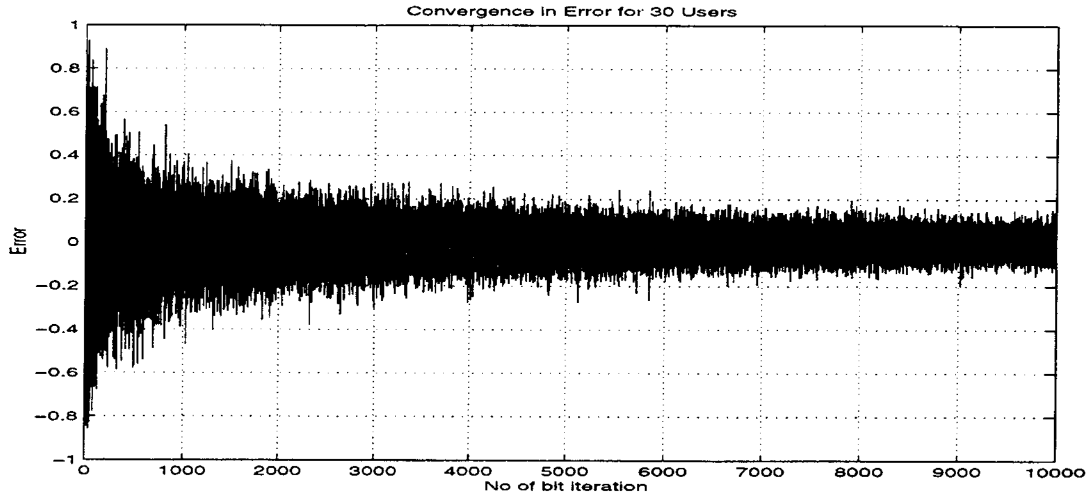


Figure 6.1 Convergence on error term using the least mean squared adaptation with 30 users present in the system

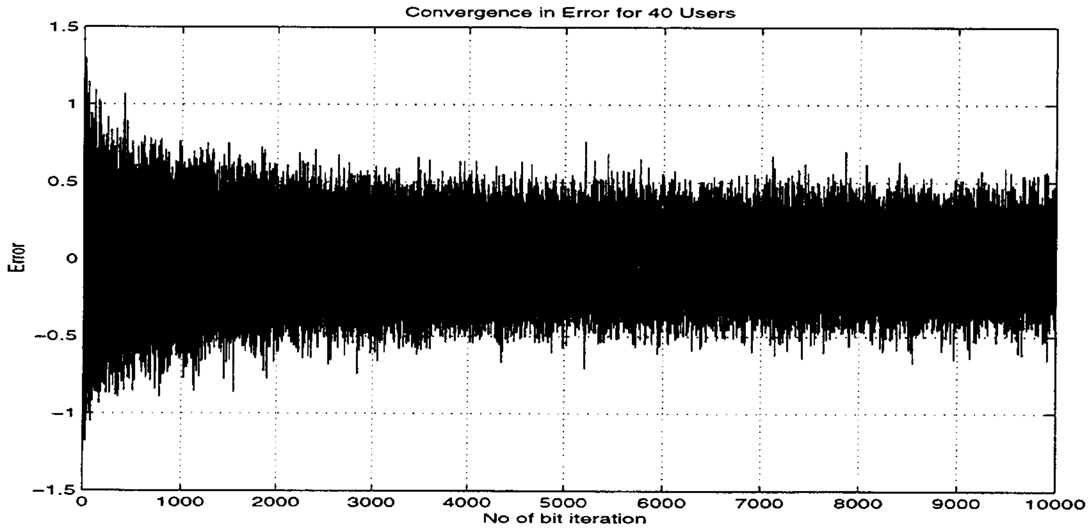


Figure 6.2 Convergence on error term using the least mean squared adaptation with 40 users present in the system

will force to keep the power control strictly constant at all time. But the use of near-far resistance demodulator allows power control to be more flexible.

The Figure 6.4 and Figure 6.7 show the convergence of the error term using the recursive least squared adaptation and the linearly constraint constant modulus algorithm. The Figure 6.8 shows the convergence in error term when blind LMS adaptation

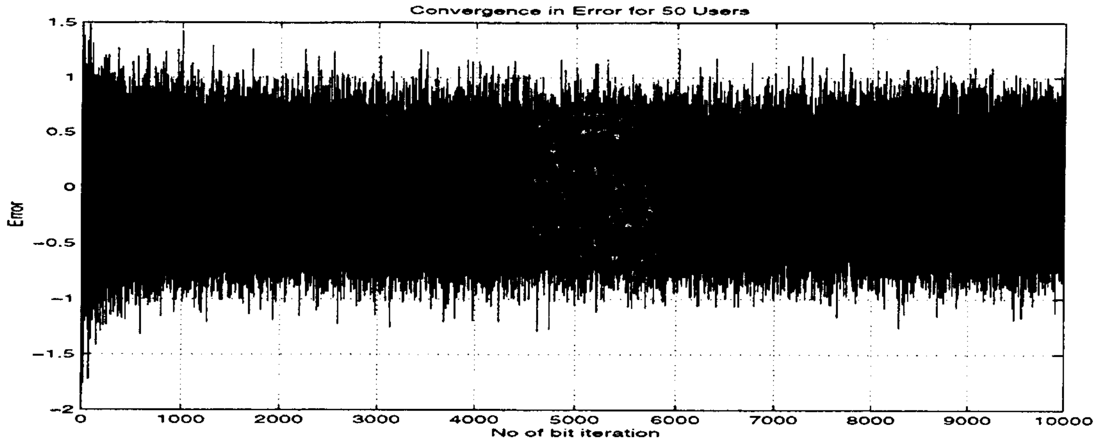


Figure 6.3 Convergence on error term using the least mean squared adaptation with 50 users present in the system

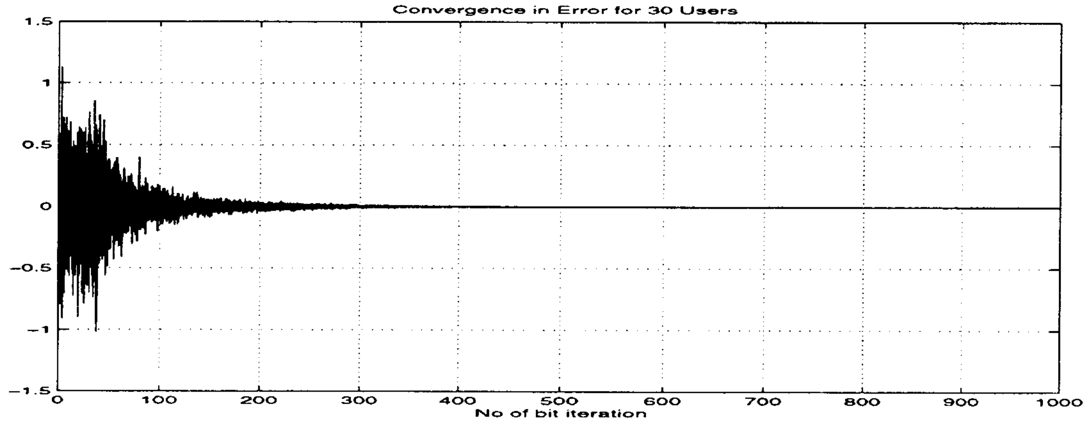


Figure 6.4 Convergence on error term using the recursive least squared ad-

is performed as mentioned in chapter 2. The simulation for all these three cases are done considering 30 users present in the system. The simulation using RLS algorithm converges completely as the total number of users considered were 30 which is less than 32, maximum allowed with perfect MAI cancellation for asynchronous case with L=63. Hence convergence for RLS method is repeated with 40 and 50 users in Figure 6.5 and 6.6. It is clear from simulation that RLS algorithm gives best performance in term of speed in convergence. The LMS adaptation with training sequence is better than the

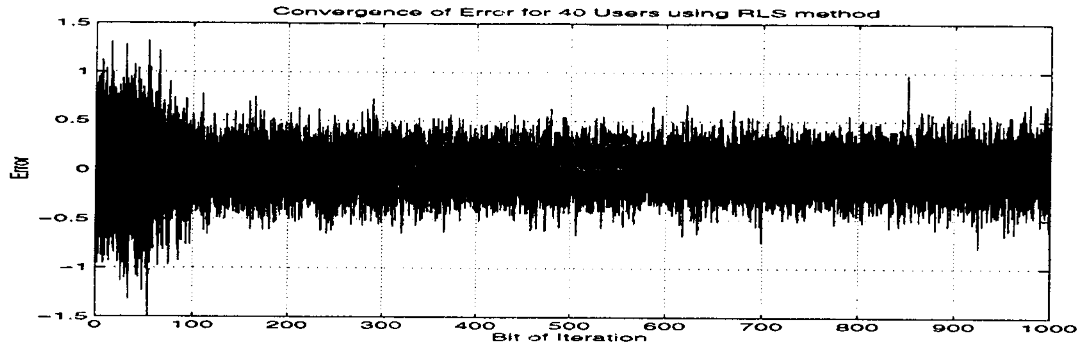


Figure 6.5 Convergence on error term using the recursive least squared adaptation with 40 users present in the system

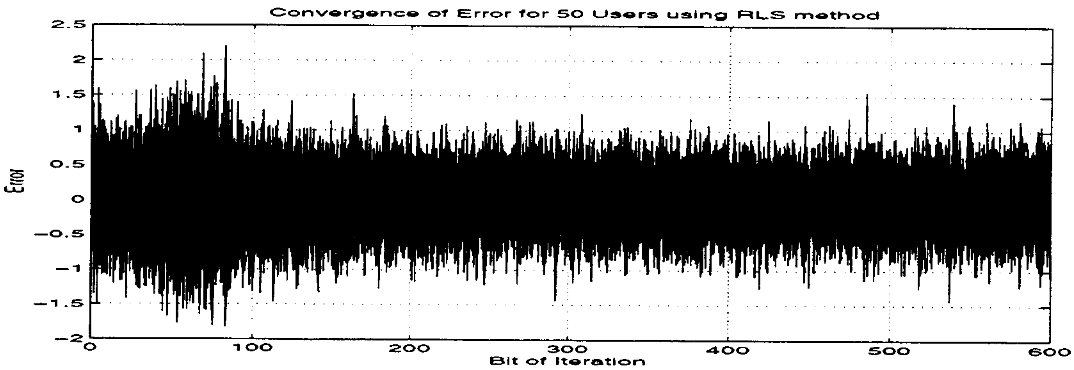


Figure 6.6 Convergence on error term using the recursive least squared adaptation with 50 users present in the system

other two blind adaptation schemes. In the following section, the bit error rate (BER) will be found using adapted coefficients along with the DFC scheme mentioned in Chapter 4.

6.3 Simulation with decision feedback cancellation scheme

For the least mean-squared adaptation, using the adapted tap-coefficients of FIR filter the bit error rates are calculated for 30 users present in the asynchronous DS-CDMA system. The BER plot is shown in Figure 6.9. The Figure 6.10 and Figure 6.11

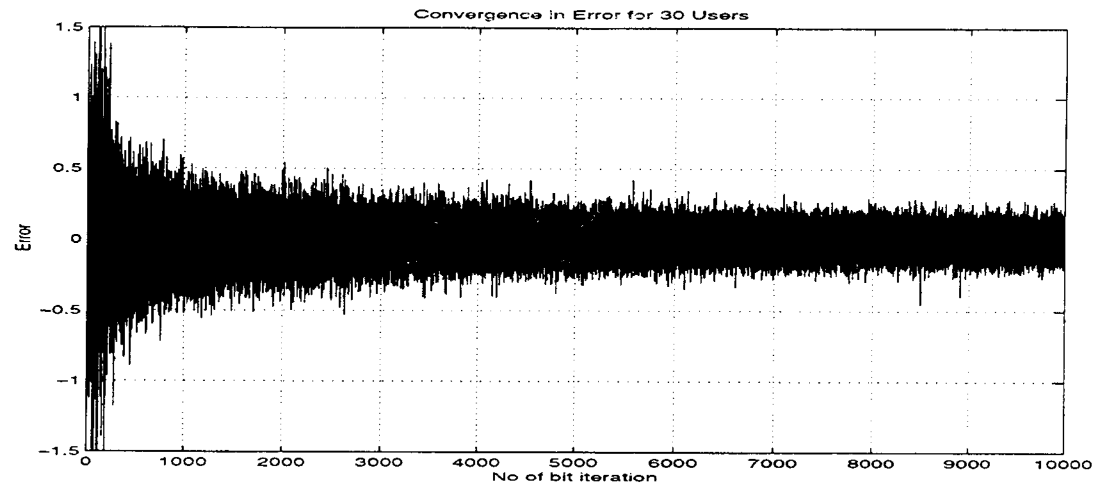


Figure 6.7 Convergence on error term using the linearly constraint constant modulus algorithm with 30 users present in the system

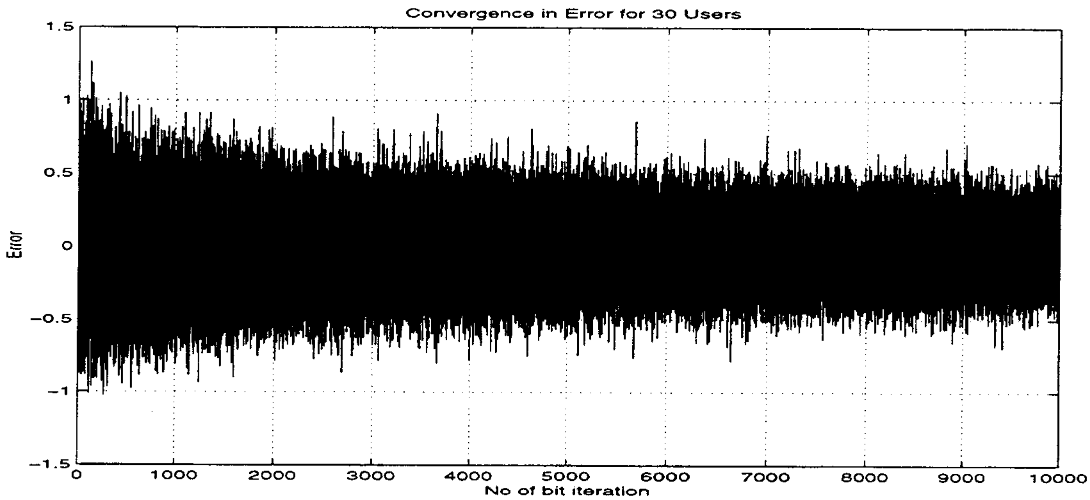


Figure 6.8 Convergence on error term using the least mean squared blind adaptation with 30 users present in the system

show the BER rate for 40 users and 50 users present in the system using the LMS adapted tap coefficients without using decision feedback cancellation. These simulation show that simple LMS adaptive multi-user detector is not immune from near-far problem in presence of large number of users in the asynchronous DS-CDMA system.

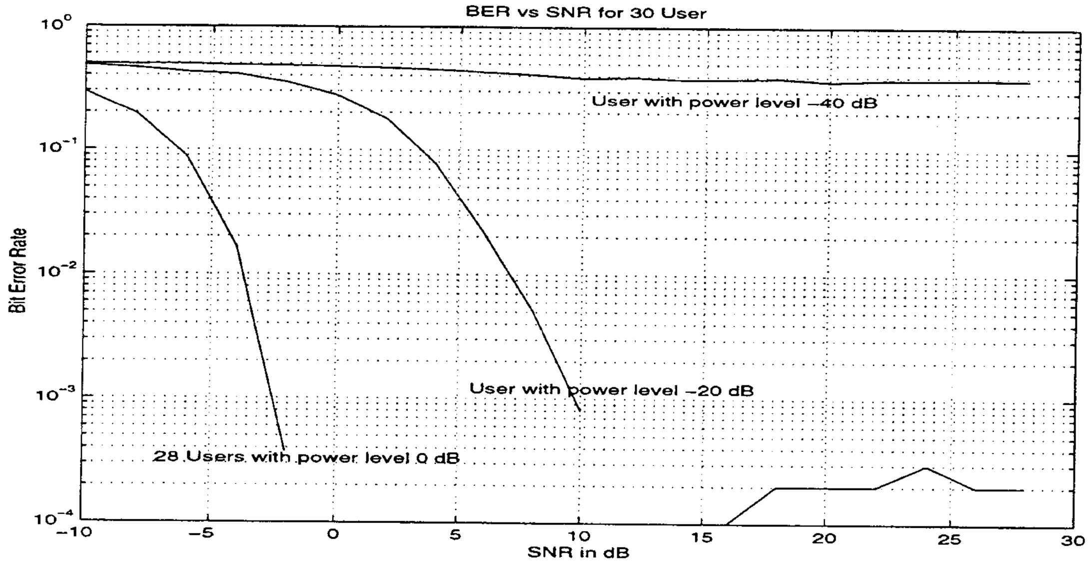


Figure 6.9 The bit error rate for 30 users present in the system using the LMS adapted tap coefficients without DFC

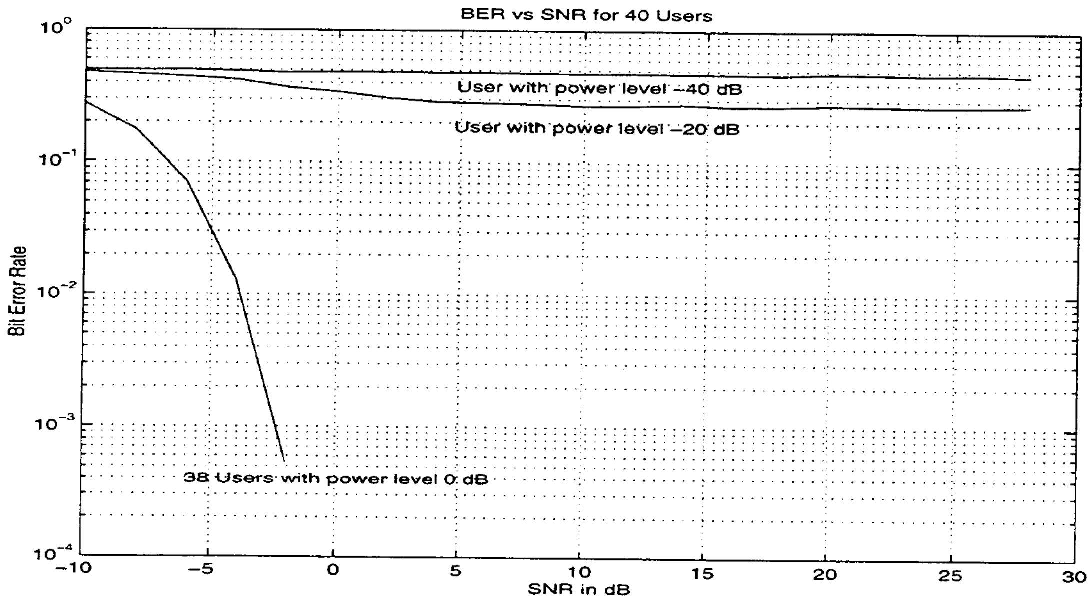


Figure 6.10 The bit error rate for 40 users present in the system using the LMS adapted tap coefficients without DFC

In chapter 4 it was mentioned that using decision feedback cancellation scheme along with the LMS adaptation will regain near-far immunity. This will be true for any adaptation process which uses the decision feedback cancellation scheme. To

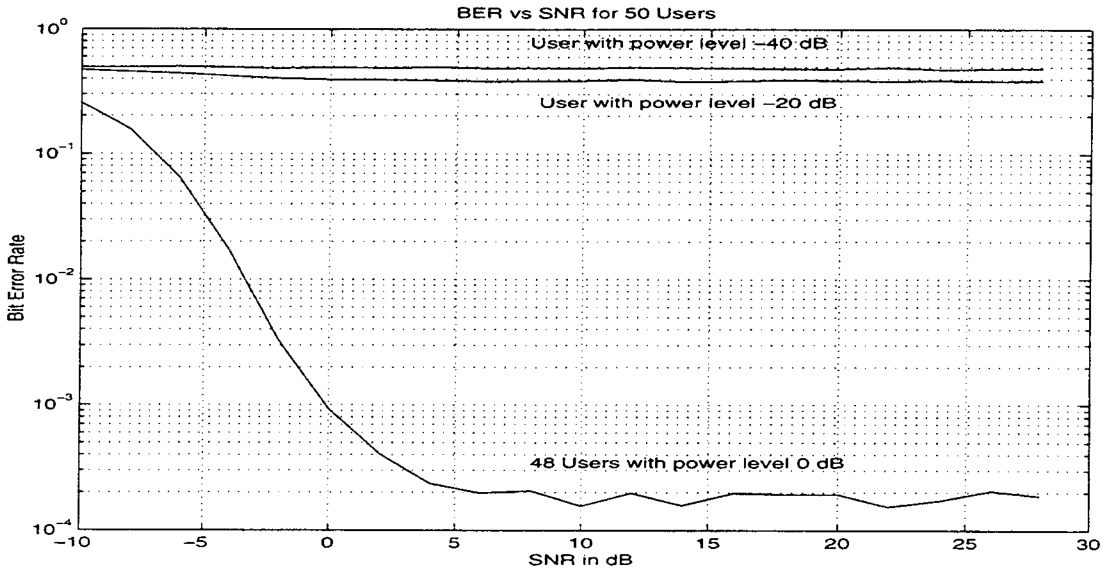


Figure 6.11 The bit error rate for 50 users present in the system using the LMS adapted tap coefficients without DFC

prove that here three cases are considered: 1) for 30 users present in the system forall three adaptive processes, 2) for 40 users present in the system and 3) for 50 users present in the system. Last two cases are considered with only LMS adapted tap coefficients. In each case, we compare bit error rate of two users whose magnitude is 0.1 and 0.01 with all other users' BER while keeping their received magnitude as 1. In other words, the received power of two users are 20dB and 40dB below as compared to all others received power.

The simulation for all three cases are repeated with different number of decision feedback cancellation stages till the near-far resistance is recovered for the users 20 dB and 40 dB below the normal power level. It is observed that as the number of users is increased from 30 to 50, the number of DFC stages which provides near-far resistance for the users 20 dB and 40 dB below normal power level for 30 users, are not sufficient

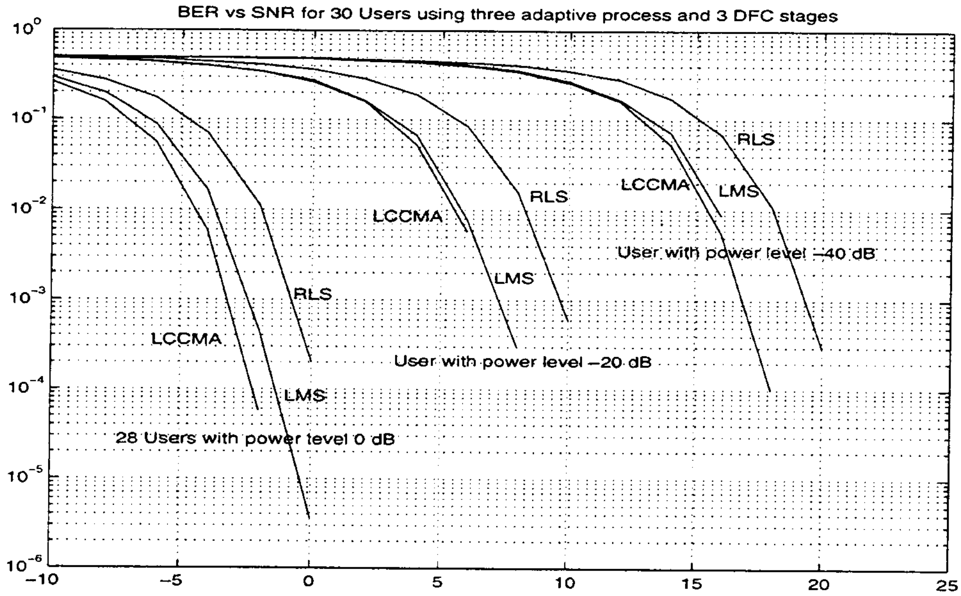


Figure 6.12 The bit error rate for 30 users present in the system using three adaptation (LMS, RLS and LCCMA) tap coefficients with 3 stages of DFC

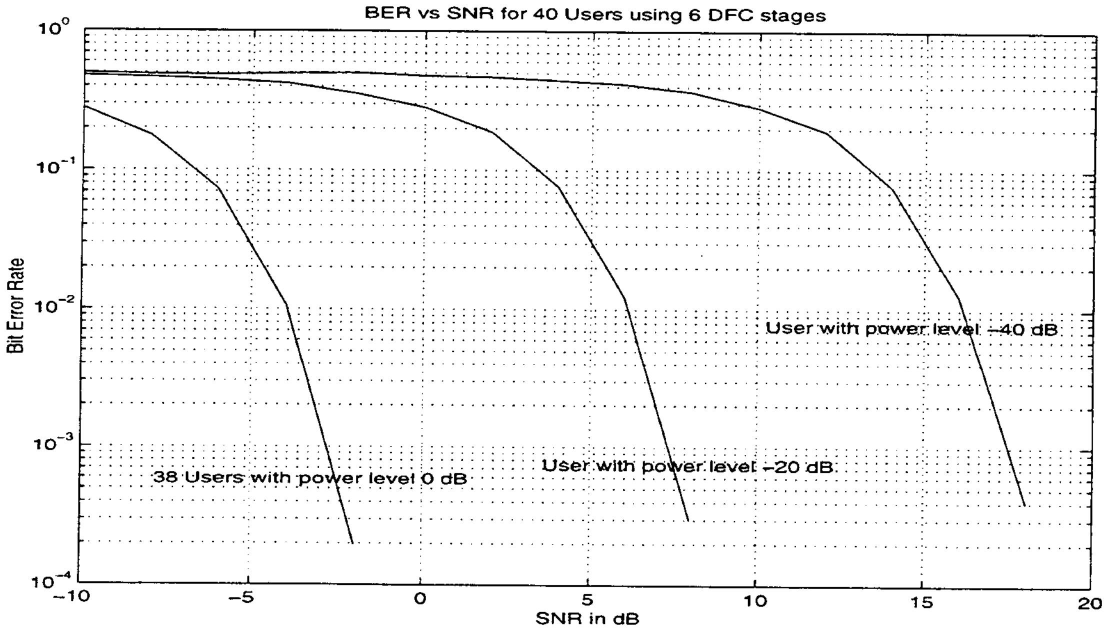


Figure 6.13 The bit error rate for 40 users present in the system using the LMS adapted tap coefficients with 6 stages of DFC

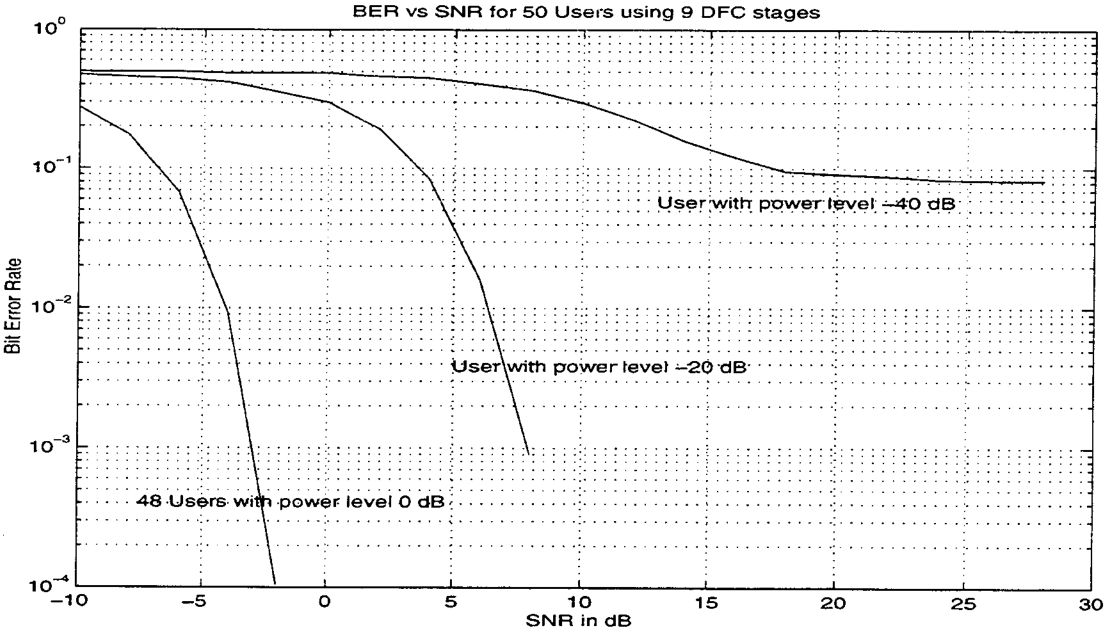


Figure 6.14 The bit error rate for 50 users present in the system using the LMS adapted tap coefficients with 9 stages of DFC

for the case with 50 users. The reason is simple. As the number of users increases, the convergence error in the LMS adaptation also increases. If the error is large, as explained in chapter 4, more number of stages required to get the same level of near-far resistance. The simulation results are plotted in Figure 6.12, Figure 6.13 and Figure 6.14 along with the theoretically predicted BER which provides the upper bound of bit error rate in Figure 6.15.

In chapter 4, it was also mentioned that, the noise in the DFC stage does not increase indefinitely. This has been proved in the series of plots in Figure 6.16, where only the additive white Gaussian noise is fed to the demodulator with nine stages of DFC using adapted tap coefficients from the LMS adaptation for 30 users. The Figure 6.17 shows that even in presence of data, noise variance does not increase beyond a

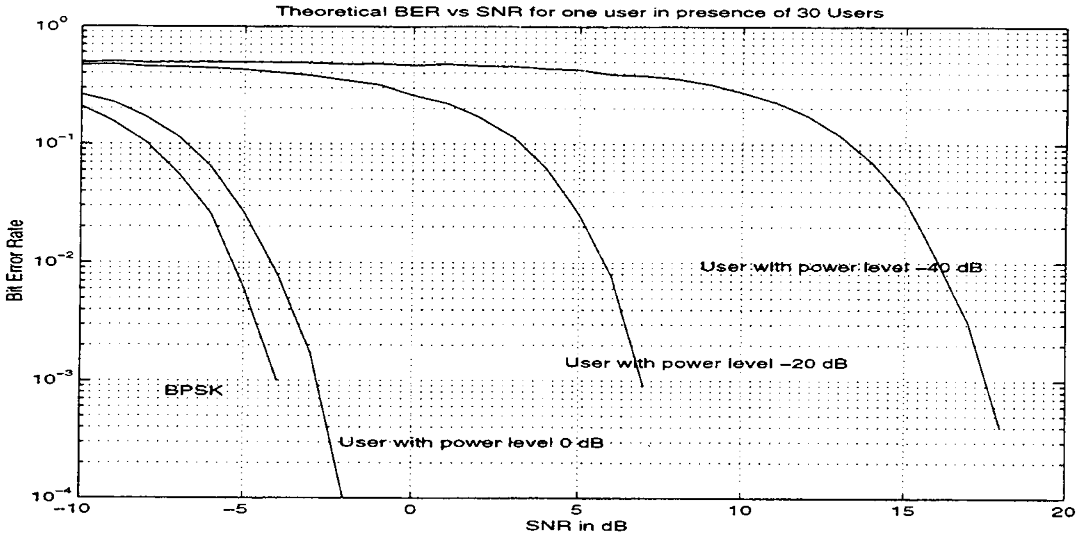


Figure 6.15 Theoretically predicted bit error rate for user 1 in presence of 30 users using the LMS adaptation with 3 stages of DFC

limit. The histograms in Figure 6.16 and Figure 6.17 show that noise statistically is equivalent in both the cases.

In the following section, simulation results are provided for bit synchronization in presence of already existing large number of users.

6.4 Synchronization

In this section, the simulation results will prove that if the length of the spreading sequence is short, it is of great help in synchronization.

The series of plots in Figure 6.18 show that by averaging over a bit period, it is possible to detect the timing of the new users. Here, for simulation, the new user's data

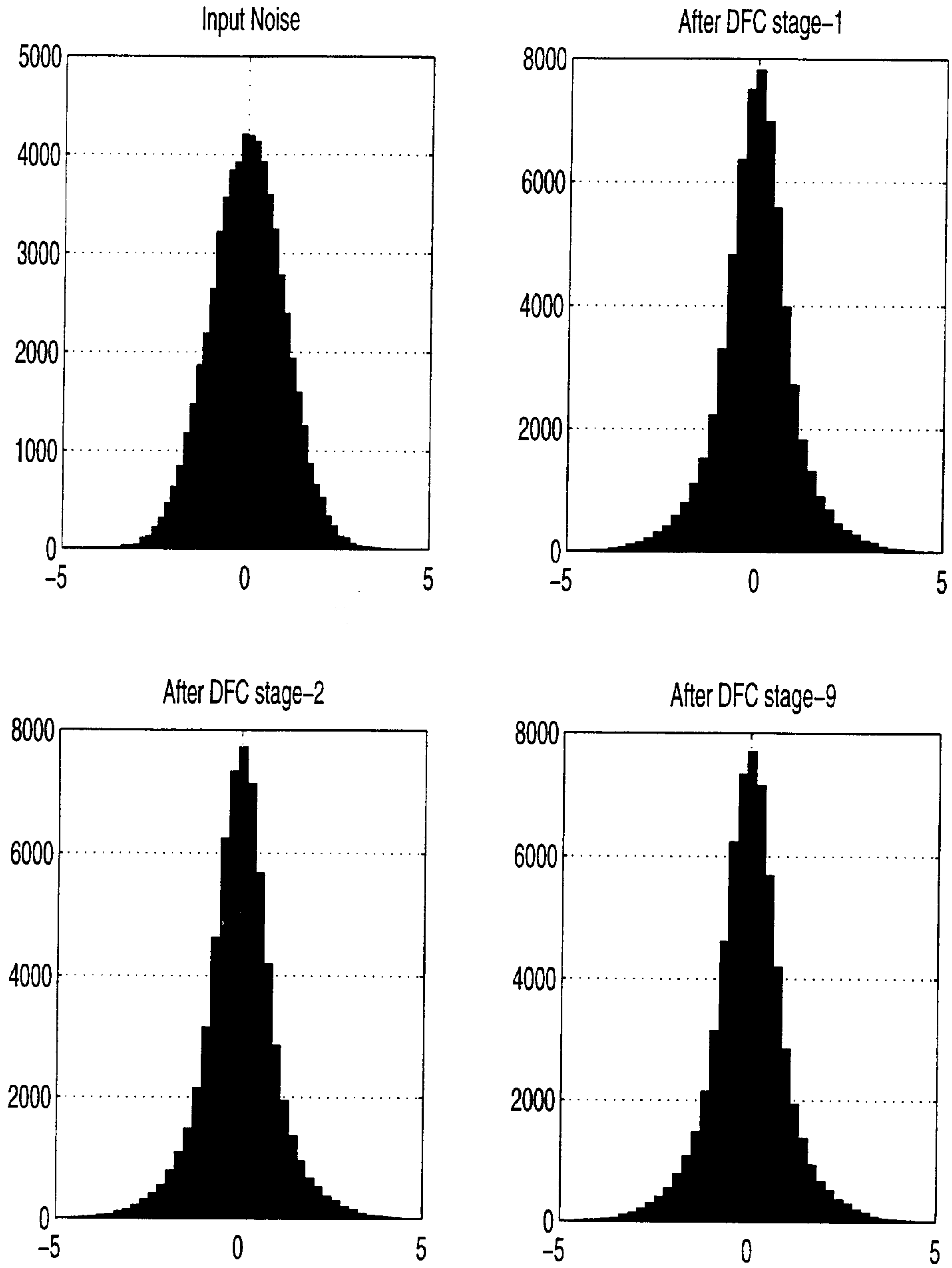
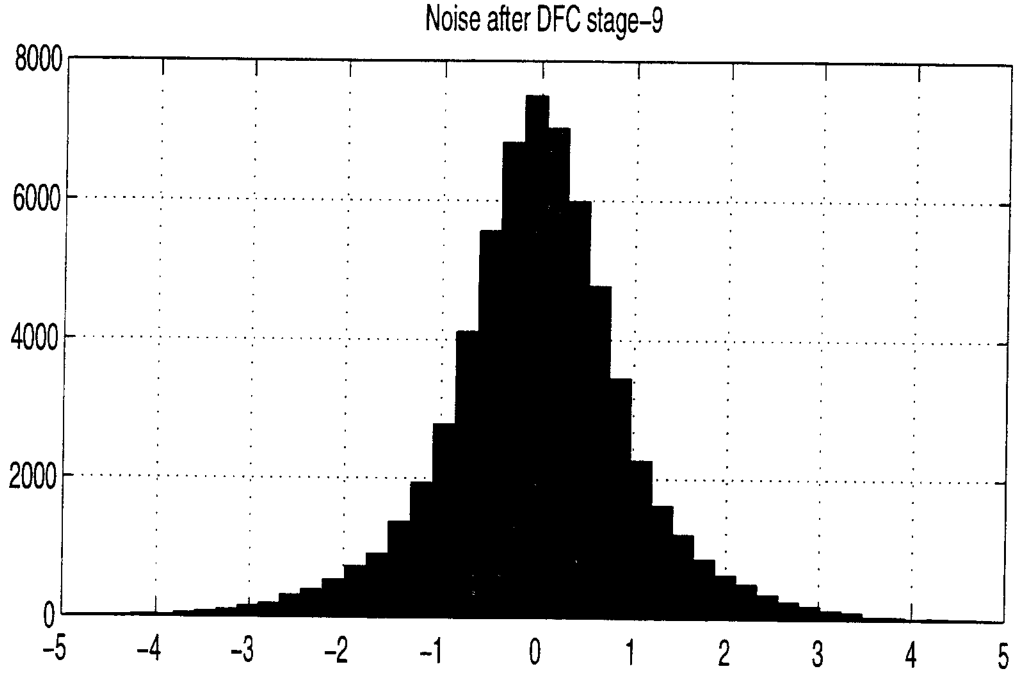


Figure 6.16 Histogram of noise in the residues after stage 1, stage 2, stage 9 of DFC blocks and of the AWGN noise with only noise of variance 1 as the input



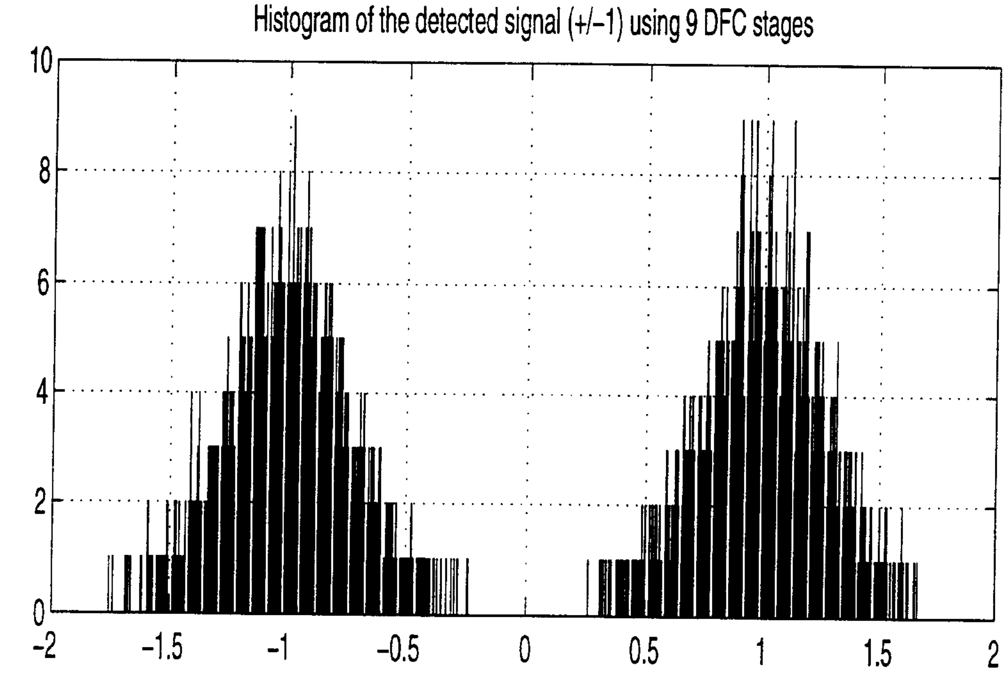


Figure 6.17 Histogram of noise (input noise is of variance 1) after DFC stage 9 and that of the detected signal (input signal +/- 1)

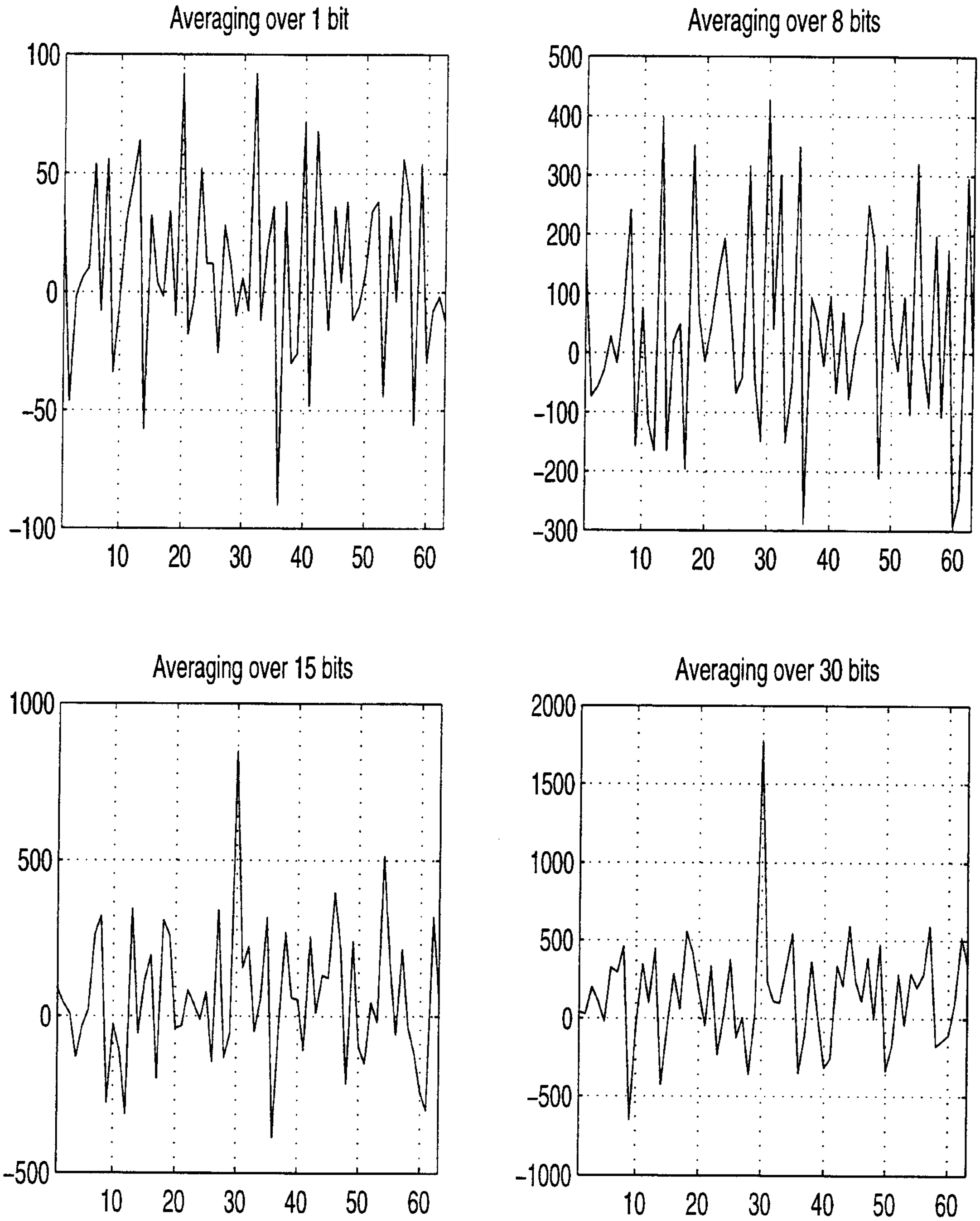


Figure 6.18 With 30 existing users, plots showing the synchronization using the method of averaging for a new user

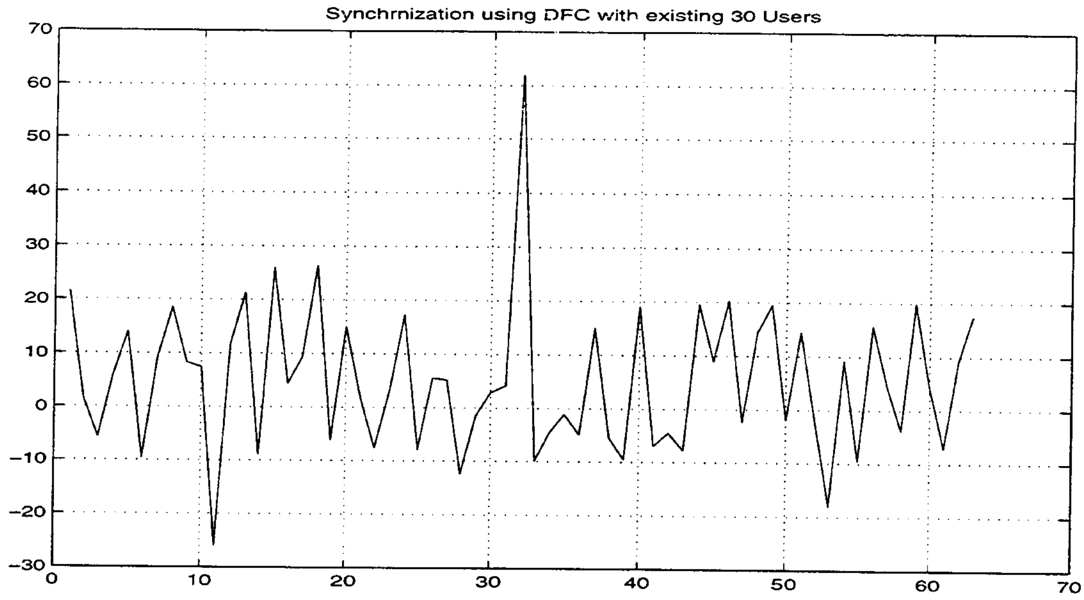


Figure 6.19 With 30 existing users, plot showing the synchronization using the method of DFC for a new user

bit is kept constant in the preamble of synchronization. Simulation is done for 30 users, when 31st is the new user.

In presence of decision feedback cancellation, the synchronization takes place in less time than that required for synchronization using averaging. The option of averaging can also be applied to make decision more robust. For the simulation, the total number of users are varied from 30 to 50 at a step of 10 when one user is added as a new comer. The synchronization is shown in Figure 6.19, Figure 6.20 and Figure 6.21.

6.5 Modulator and demodulator for QPSK transmission

The modulation and demodulation considered in the simulations previously mentioned use the Binary Phase Shift Keying (BPSK) method of transmission at base-

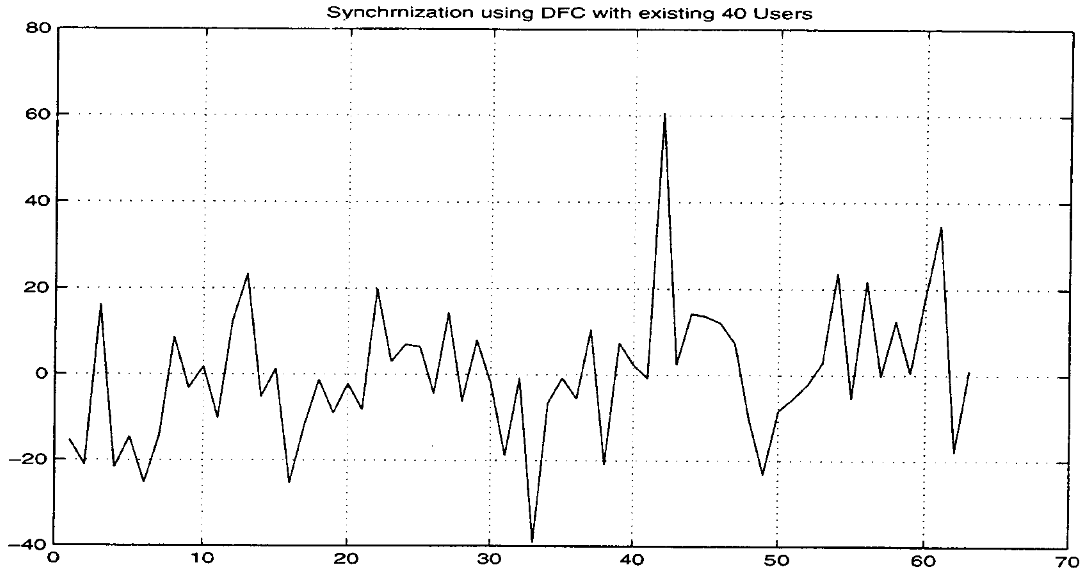


Figure 6.20 With 40 existing users, plot showing the synchronization using the method of DFC for a new user

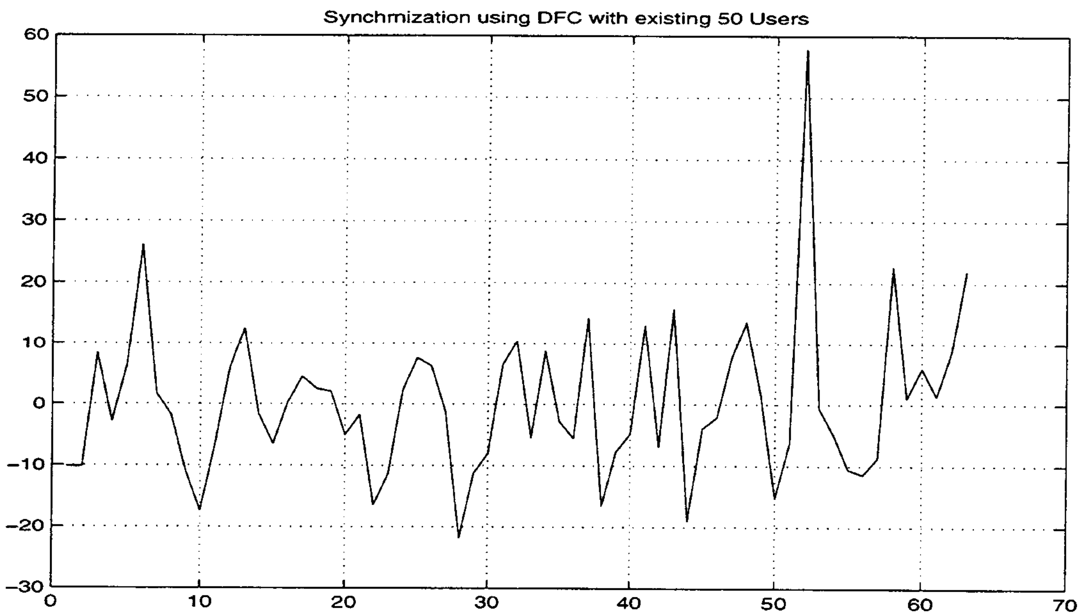


Figure 6.21 With 50 existing users, plot showing the synchronization using the method of DFC for a new user

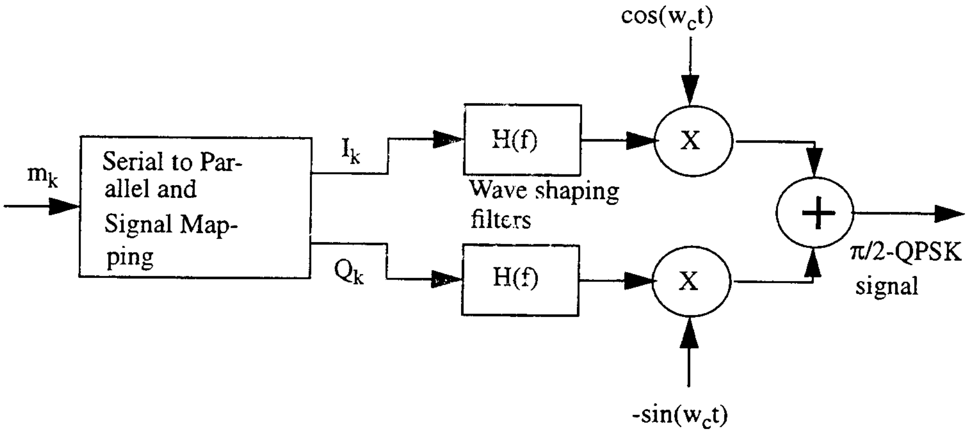


Figure 6.22 π/2 QPSK modulator structure

band. Normally in practice the Quadrature Phase Shift Keying (QPSK) is used instead of BPSK, as QPSK has twice the bandwidth efficiency of BPSK. In this section, a modified QPSK will be proposed for asynchronous DS-CDMA transmission. In π/4-QPSK the transmitted signal in inphase (I) and quadrature (Q) takes value out of +/- 1, +/- 0.707 and 0. Hence the received signal in I and Q also has five levels of magnitude. In DS-CDMA reverse link, the receiver at base station receives all individually transmitted data simultaneously in asynchronous form. It would be advantageous if the individual I and Q varies between only +/- single level of magnitude. Thus by taking the absolute of I and Q, it will be possible to track the amplitude of the received signal continuously. Also, it will help in frequency synchronization. The required modification is done on the existing π/4-QPSK transmission technique and the modified technique may be called π/2-QPSK transmission.

A block diagram of the proposed transmitter is shown in Figure 6.22. The input bit stream is partitioned by a serial-to-parallel converter into two parallel data streams $m_{I,k}$ and $m_{Q,k}$ each with a symbol rate equal to the half that of incoming bit rate. The kth in-phase and quadrature pulses, I_k and Q_k, are produced at the output of the signal mapping circuit over time $kT \le t \le (k+1)T$ and are determined by their previous values, I_{k-1} and Q_{k-1}, as well as θ_k, which itself is function of ϕ_k. The ϕ_k is a function of the current input symbols $m_{I,K}$ and $m_{Q,k}$. The I_k and Q_k represent rectangular pulses over one symbol duration having amplitudes given by $I_k = \cos(\theta_k)$ and $Q_k = \sin(\theta_k)$, where, $\theta_k = \theta_{k-1} + \phi_k$ with $\theta_0 = \pi/4$. The phase shift ϕ_k is related to the input symbols $m_{I,k}$ and $m_{Q,k}$ according to table 1. The I_k and Q_k unlike $\pi/4$-QPSK take only +/- 0.707, thus in demodulator the received amplitude for each user remains constant in the absence of fading with change in sign. The in-phase and quadrature bit

Table 6.1 Carrier Phase shifts corresponding to various input bit pair.

Information bits $m_{I,k}$ and $m_{Q,k}$		Phase shift ϕ_k
1	1	0
0	1	$\pi/2$
0	0	π
1	0	$-\pi/2$

streams I_k and Q_k are then separately modulated by two carriers with radian frequency of ω_c which are in quadrature with one another to produce the final waveform given by,

$$s(t) = I(t)\cos(\omega_c t) - Q(t)\sin(\omega_c t) \tag{119}$$

In reality both I_k and Q_k are usually passed through raised cosine roll off pulse shaping filters before modulation, in order to reduce the bandwidth occupancy. But in simulation, the raised cosine filters are not considered.

Due to ease of hardware implementation, the differential detection is employed to demodulate the transmitted signal using $\pi/2$-QPSK techniques. This demodulation procedure as shown in Figure 6.23 does not rely on phase synchronization. This demodulation, at first, use the decision feedback cancellation method in baseband I and Q branches to get the transmitted I and Q component for an individual user. If $\phi_k = \tan^{-1}(Q_k/I_k)$ is the phase of the carrier due to the k^{th} data bit, the output of the DFC stages will be v_k and z_k in in-phase and quadrature arm of the demodulator. For one user, the DFC output in I and Q branch can be expressed as $v_k=\cos(\phi_k - \gamma)$ and $z_k=\sin(\phi_k - \gamma)$. The γ is a phase shift due to noise, propagation and interference. It is assumed that the change in γ will be much slower than ϕ_k so essentially it is a constant. The two sequences v_k and z_k are passed through a differential decoder which operates on the following rule,

$$X_k = v_k v_{k-1} + z_k z_{k-1} \tag{120}$$

$$Y_k = z_k v_{k-1} - v_k z_{k-1} \tag{121}$$

The output of the differential decoder can be expressed as $X_k = \cos(\phi_k - \phi_{k-1})$ and $Y_k = \sin(\phi_k - \phi_{k-1})$. From table 1 it follows that the constellation of X_k and Y_k will be on 0 and +/-1 and thus it will be difficult to take decision. To get the decision

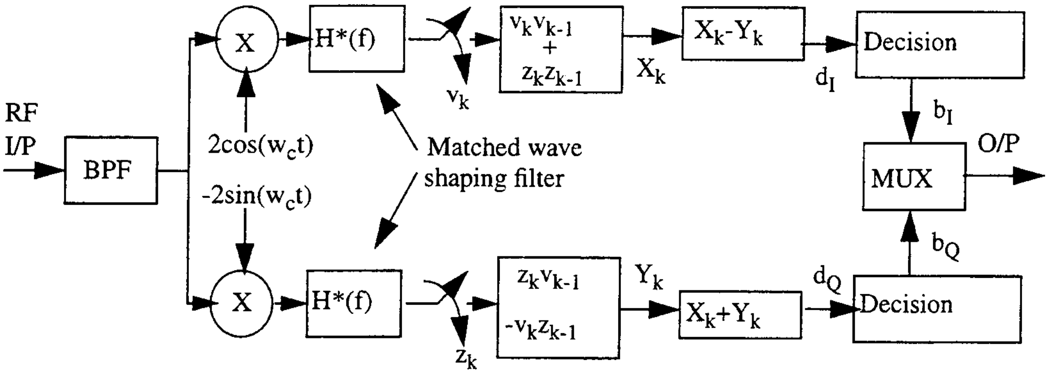


Figure 6.23 π/2 QPSK demodulator structure

level at 0, the X_k and Y_k signals are passed through an adder and subtractor circuit. The the output will be $d_I = X_k - Y_k$ and $d_Q = X_k + Y_k$ which provides the needed π/4 shift. The decision block implements the logic, if $d_{I,Q}>0$ (or $d_{I,Q}<0$), then $b_{I,Q} = 1$ (or $b_{I,Q} = 0$). Following that the parallel to serial block is required to convert the I/Q signals into a single bit stream.

Chapter 7. Summary and Areas for Future Investigation

It must be clear by this time, when in absence of channel noise and channel fading (Rayleigh and time dispersive fading), a total number of users K, are transmitting their signals (in bits) modulated by their own signature sequence (here they will be Gold sequences), the base station will receive a signal all added together with unknown time delays. This unknown time delay of each user is correctly found out by synchronization procedure. Now, with the knowledge of signature sequence and time delay for each user in the base station, one needs to calculate a coefficient sequence corresponding to desired user's signature sequence such that the inner product of the received signal and the coefficients with right bit starting point will result into the desired signal amplitude along with sign and with no multiple access interference (MAI) term present in the inner product term. But, if the total number of users in asynchronous transmission become larger than 32 when the length of chip sequence considered is 63 for a bit period, the total annihilation of MAI term in the inner product is not possible which calls for a technique called decision feedback cancellation. The DFC scheme allows the MAI term to become as small as possible in exchange for added hardware complexity of adding multiple number of DFC stages even if the number of users is more than 32.

As the addition of individual users signal produces the resultant signal at base station, the received signal retains the linear characteristics. That means, by solving simple linear equations, one can solve to find the desired coefficients, which produces perfect near-far immunity as long as total number of users is less that 32. Also, as it is a linear system, the least mean square recursive solution produces a solution, which provides the best bit error rate characteristics in the linear sense. Here, a nonlinearly optimized system is also considered which is called linearly constraint constant modulus algorithm and it is found that it provides the best bit error rate characteristics in simulation.

One more new concept is proposed here, that is amplitude estimation instead of equalization. If the adaptation takes place on the received signal, it will result into equalization. Instead of that if the adaptation takes place on the generated received signal created on the basis of delay time and signature sequence of all users, it will result into amplitude estimation. In the process of equalization, the adapted tap-coefficients will depend on the channel noise and the channel fading. But the amplitude estimation does not depend on channel noise and fading. The amplitude estimation correctly produces the amplitude for each user at a delay of chip time period (or by the sampled time period of the chip). Thus, for each user, for a transmitted bit the base station will form a time dispersed collection of amplitudes, and the strongest among those estimations will be chosen for decoding. Also, unlike equalization, for amplitude estimation, the adaptation process has to converge only once until an existing user leaves or a new user joins the existing users. But, whatever method is used for finding out the tap coefficients, decision feedback cancellation scheme can always be used to increase the total number of users in the system.

Simulation results indicate that among three adaptive methods (the least mean squared adaptation, the recursive least squared adaptation and the linearly constraint constant modulus algorithm) the LCCMA gives the best bit error rate. It is also found that if the criterion to judge the performance is to get minimum number of decision feedback stages, then the RLS algorithm fares best as it produces the minimum convergence error for a fixed number of users present in the system. If the criterion is to have minimum hardware complexity, then the LMS adaptation performs better than any other algorithm. The convergence in error for all three adaptive methods shows the necessity to have decision feedback cancellation in presence of large number of users in the system. The theory and simulation produce almost similar bit error rate for single user in presence of 30 users in the system.

Simulation results also point out that the noise in the DFC stages does not increase beyond a limit as it has been explained in the theory. Hence addition of several number of DFC stages improves the near-far resistance of the demodulator.

Simulations on synchronization show that usage of the proposed demodulator improves the bit-timing synchronization. Also the $\pi/2$ QPSK demodulator improves the chance of frequency synchronization using Costas loop [1].

The theoretical results shows that the all three adaptive methods along with DFC stages not only provides near-far resistance but their overall bit error rate performances are very near to the performance of BPSK bit error rate.

The further study in this area can be divided into six categories:

1. Increase in the number of users by usage of longer chip sequence covering more than one transmitted bit and consideration of time dispersive multi-path fading.

2. To find the steady state analysis of LCCM algorithm and search for the best adaptive

algorithm in terms of hardware complexity, bit error rate, convergence in error and ease in finding the step size if it is required for the algorithm to be used.

3. To find whether adaptive methods using decision feedback (DF) can increase the capacity.

4. To obtain simulation result with the raised cosine filter and $\pi/2$ or $\pi/4$ QPSK modulation and demodulation with different sampling rate at the demodulator to find which will provide better performance.

5. To include error correcting code in the simulation and to find the best error correcting code that will give the best bit error rate performance for the proposed demodulator.

6. To obtain better chip sequence which produces better results in terms of error in convergence and bit-timing synchronization.

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