BLIND ADAPTIVE MULTIUSER DETECTION WITH INTEGRATED CHANNEL ESTIMATION FOR MULTIPATH CDMA CHANNELS

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Certificate

This is to certify that the thesis entitled "**Blind adaptive multiuser detection with integrated channel estimation for multipath CDMA channels**" is a bonafide record of the work done by **Sri. ALI.C. K**, under my supervision. The thesis is submitted to the University of Calicut in fulfilment of the requirement for the award of the degree of Doctor of Philosophy in Communication Engineering. The results contained in this thesis have not been submitted to any other University or Institute for the award of any degree or diploma.

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ABSTRACT

An adaptive, blind multiuser detector with integrated channel estimation for digital wireless networks in synchronous code division multiple access (CDMA) channels is developed and analysed. The detector is formed iteratively from the received signals using the minimum output energy (MOE) criterion. This detector is blind in the sense that no signature codes of the interfering users, amplitude of the received signals, channel parameters of users etc. are assumed known. The detector uses only the signature code of the desired user and his/her timing. Moreover no pilot sequences are required to train the detector. The computational complexity involved in the formation of the detector is very low compared with the competing methods. The performance of the detector was found to be on par with a non-adaptive, non-blind ideal minimum mean-square error (MMSE) detector implemented with the knowledge of the signature code of the interfering users, amplitude of the received signals, channel parameters etc. The proposed receiver collects energies of the desired user's signals that reach the receiver via different paths and combine them as done by a conventional RAKE receiver. Because of this the bit error rate (BER) performance of the receiver is far better than a receiver, which collects only the single path energy in a multipath scenario. By using multiuser techniques, multiple access interference (MAI) is almost eliminated from the system. The detector is capable of operating in dynamic channel scenarios (fading channel, channel in which users enter and exit) and is thus adaptive in nature.

In the proposed method the decorrelating or MMSE filters corresponding to each path of the desired user/user of interest (UOI) is first determined in a blind, adaptive manner using MOE criterion and least mean square (LMS) algorithm. The

obtained filter for each path is approximately MAI free. In order to combine energies of all paths of the UOI, the received signal is projected onto the subspace spanned by these filter vectors, to get the final filter. Thus in order to remove MAI, the output energy is minimized using the MOE criterion and subsequently the signal energy maximized to improve the SNR. This max/min approach is applied in this work. The obtained filter varies slightly from symbol to symbol because of noise. To get a noise-free filter, the eigen vector of the co-variance matrix of the projected signal is computed. The computation of the eigen vector is also done adaptively using the rank-one, projection approximation subspace tracking by deflation (PASTd) algorithm to suit the method for dynamic channels.

The performance of the proposed detector is analyzed and validated under various scenarios. The performance of the detector is first compared with detectors based on the subspace and recursive least squares (RLS) methods in a single path case. It is verified that the proposed method excels the subspace method and RLS method both in terms of BER performance and computational complexity. The proposed detector is then compared with an RLS based detector in a multipath scenario and found to outperform in terms of BER performance and computational complexity. The performance of the detector is also tested in a multipath fading mobile channel where the characteristics of the channel changes with time. The proposed detector is found to work without much performance degradation in a mobile channel. It is seen that the performance of the proposed detector in a mobile channel is close to that of an ideal MMSE detector used in an identical channel without fading.

As a supplementary work, an unbiased, blind channel estimation scheme is developed using the results from the proposed work. Some simple, related works are also reported as by-products of the main work. They include a blind adaptive decorrelating detector, which is not possible, using existing methods. A simple fading-free decorrelating detector also is formed which can operate without much up-dation in a fading channel. A robust detector was also configured, which can be used in cases of signal mismatch and channel distortions. We are also presenting a novel technique for improving the channel capacity of a CDMA system, which uses orthogonal codes.

As a future work the proposed method can be extended to asynchronous CDMA systems, which do not require the knowledge of the timing offsets of the desired user. The proposed method also can be applied in multiple input multiple output (MIMO) systems where the transmitters and receivers are fitted with multiple antennas.

Major contributions of this work are the following

1. An adaptive, blind multiuser detector for single-path channels with reduced computational complexity is developed and performance is compared with ideal MMSE detector and with existing methods like subspace and RLS methods.
2. The single-path work is extended to multipath scenario without explicit channel estimation and performance is compared with ideal MMSE detector and with RLS method.
3. The proposed multipath detector is tested in multipath fading channels and obtained improvement in performance.

4. An unbiased, blind, adaptive channel estimation scheme is developed, using the results from the proposed work.
5. A few related minor works are also reported.

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LIST OF SYMBOLS

Greek

μ	Step-size parameter of the LMS algorithm
ρ	Normalized correlation coefficient between two codes
$\varphi(t)$	Chip waveform
λ_c	Wavelength of the carrier
$\varphi_c(\tau)$	Auto-correlation function
$\varphi_c(\Delta f)$	Auto-correlation function in the frequency domain
ρ_{ij}	Normalized cross correlation between the codes of the *i*th and *j*th user.
τ_k	Propagation delay of the *k*th user
$\alpha_l(t)$	Time varying signal envelope of the *l*th path
$\tau_l(t)$	Time varying propagation delay of the *l*th path
$\theta_l(t)$	Time varying phase of the *l*th path
σ^2	Variance of noise

English

$\hat{h}_{kl}(n)$	Estimated channel gain of the k^{th} user for the l^{th} path during the n^{th} symbol
$\tilde{s}$	Effective signature vector
$\sum s$	Singular values of signal subspace

$\mathbf{W} \in R^{Nxr}$	**W** is a real N x r matrix
$\mathbf{r} \in R^{N}$	The vector **r** is an element of the real vector space with dimension N
$\mathbf{r} \in C^{N}$	The vector **r** is an element of the complex vector space with dimension N
$\lVert\mathbf{x}\rVert$	Norm of the vector **x**
$(\Delta f)_c$	Coherence bandwidth of the channel
$(\Delta t)_c$	Coherence time of the channel
$<\mathbf{x}_1, \mathbf{x}_2>$	Dot product of two column vectors $\mathbf{x}_1$ and $\mathbf{x}_2 = \mathbf{x}_1^H\mathbf{x}_2$
A	Diagonal matrix for the received amplitudes of the users' signal
b	Column vector for the users' bits
B_d	Doppler spread of the channel
b_k	Data bit of the *k*th user
D	Blocking matrix
diag(**x**)	Matrix with diagonal as **x**
$\mathbf{d}_k$	Decorrelating detector for the *k*th user
E[.]	Statistical expectation
f_c	Carrier signal frequency
f_d	Doppler shift in frequency
g	Column vector of dimension L
G	An LxL square matrix
$h(\tau, t)$	Time varying low-pass impulse response of the channel
$h(f,t)$	Time varying transfer function of the channel
$\mathbf{h}_k$	Discrete channel response of the *k*th user
h_{kl}	Complex channel gain of the *l*th path of the *k*th user

$\mathbf{I}_N$	Identity matrix of dimension N
K	No: of users
$\mathbf{k}(n)$	Kalmann filter gain during the *n*th symbol
L	No: of multipaths
M	No: of symbols considered
$\mathbf{m}_k$	Multiuser detector for the *k*th user
$\mathbf{m}_{mse}$	Ideal MMSE detector
$\mathbf{m}_{mv}$	Minimum variance detector for the first user
$\mathbf{m}_r$	RLS based detector
$\mathbf{m}_s$	Subspace based detector
$\mathbf{n}$	Noise vector
n	Symbol index
N	Length of the signature code=Processing gain
n(t)	Noise waveform
P	Over sampling factor
$\mathbf{r}$	Received signal in vector form
R(**D**)	Range space of the columns of the matrix **D**
r(t)	Received waveform of all users plus noise
$\mathbf{R}_c$	Normalized cross correlation matrix of signature codes
Re	Real part
$\mathbf{S}$	Matrix for delayed signature codes of a user
s(t)	Super position waveform of all users
$SINR_{mse}$	Signal to interference plus noise ratio for the MMSE detector
$\mathbf{s}_k$	N-dimensional column vector for the signature code of the *k*th user

$s_k(t)$	Signature waveform of the *k*th user
$\mathbf{s}_{kl}$	Signature code of the *k*th user delayed by (*l*-1) chips
T	Symbol duration
T_c	Chip duration
T_m	Multipath spread of the channel
$\mathbf{U}_o$	Unitary matrix spanning a space orthogonal to the signal subspace
$\mathbf{U}_s$	Unitary matrix spanning signal subspace
$\mathbf{v}$	The principal eigen vector of the co-variance matrix **Y**
v_m	Velocity of the mobile
W	Bandwidth of the signal
$\mathbf{x}(n)$	Value of the vector **x** during the *n*th symbol interval
$(.)^*$	Conjugate
$(.)^T$	Transpose
$(.)^H$	Conjugate transpose
$\lceil x \rceil$	Smallest integer greater than or equal to x
$\lfloor x \rfloor$	Largest integer less than or equal to x
$\mathbf{x}_k$	Vector orthogonal to $\mathbf{s}_k$ such that $<\mathbf{s}_k,\mathbf{x}_k>=0$
$\mathbf{Y}$	Co-variance matrix of the whitened observables
$\mathbf{y}$	Column vector for the o/p of the bank of correlators
$\mathbf{y}_w$	Whitened observables

ABBREVIATIONS

AMPS	American mobile phone system
BER	Bit error rate
CDMA	Code division multiple access
CMF	Conventional matched filter
CMMSE	Constrained MMSE
EVD	Eigen value decomposition
GSM	Global system for mobile
IMTS	International mobile telecommunication system
ITU	International telecommunication union
LMS	Least mean square
MAI	Multiple access interference
MMSE	Minimum mean squared error
MOE	Minimum output energy
MPI	Multipath interference
MSC	Mobile switching centre
MUD	Multiuser detection
O (N)	Of the order of N
PASTd	Projection approximation subspace tracking by deflation
PCS	Personal communication system
PIC	Parallel interference cancellation
RLS	Recursive least square
SIC	Serial interference cancellation
SVD	Singular value decomposition
UMTS	Universal mobile telecommunication system
UOI	User of interest

Chapter 1

INTRODUCTION

1.1 INTRODUCTION

Wireless communication field has been witnessing dramatic changes in the recent past. The mobility and flexibility offered by a mobile/portable terminal make it the technology of the millennium. So far, mobile terminals were mainly used for voice transmission and low speed data transmission. However, if it has to survive as a competing system with wired networks, it should be capable of offering Internet and multimedia services.

Code division multiple access (CDMA) implemented with direct-sequence (DS) spread-spectrum is among the most promising multiplexing technologies for wireless telecommunication services and is better than TDMA/FDMA systems. In this system, all users transmit at the same time and frequency but use distinct signature sequences to allow signal separation at the receiver. Simultaneous spectrum sharing, mitigation of jamming and multipath fading are the unique features of DS/CDMA. To satisfy ever-increasing demands for high data rates, as well as to allow more users to simultaneously access the network, interest has peaked in the so called wideband CDMA (WCDMA). While conventional CDMA is used in the second-generation mobile systems, WCDMA has been selected as the main air-interface for the third-generation mobile systems both, in Europe & Japan.

The wireless channel is basically hostile to transmitted signals compared to wired channels. The main disturbances in a multiple-user wireless environment are multiple access interference (MAI) and multiple path interference (MPI), apart from noise. These interferences increase with the increase of data rate. Unless these disturbing phenomena are properly addressed, the dream of multimedia and high rate data via wireless network will not be realised. Because the cross correlations between the signature sequences for different users are nonzero, a nearby interferer can disrupt reception of a highly attenuated desired signal resulting in near-far effect. The conventional single user matched filter (conventional matched filter) receiver fails to combat MAI and hence prone to near-far effect in a mobile scenario. It has been demonstrated that multiuser detection provides very substantial performance gains over detection techniques conventionally used in multi-access channels. Because of this, multiuser detection is the proposed detection strategy for the third generation. Universal Mobile Telecommunication System (UMTS) and the Japanese WCDMA system [1]. The optimal multiuser detector for CDMA systems has exponential computational complexity and hence, sub-optimal detectors like decorrelating detectors (decorrelators), minimum mean squared-error (MMSE) detectors, the successive cancelling detectors, the multistage detectors and the decision-feedback detectors are more popular. Optimal performance with linear processing can be achieved only when all spreading codes are orthogonal or when only one user exists. Even though multiuser detectors are MAI free they are not free from MPI. In order to overcome MPI the principle of RAKE receivers (conventionally used in single user receivers) can be extended to the multiuser case also.

Multiuser detection strategies for DS/CDMA have been extensively investigated over the past 15 years. The most prominent results in this area include the finding that it is the thermal noise, and not the MAI, that decides the ultimate performance-degrading factor of such systems. It is widely recognized that MAI exists even in perfect power controlled CDMA systems and multiuser detectors perform better than the conventional matched filter (CMF) in such situations. The non-adaptive multiuser receivers are determined based on the signature codes of different users, the amplitude of users' signal, timing of signals, channel impulse response etc. In this case, detection algorithms involve matrix multiplications and inversions and require block based computations and floating point accuracy, which significantly increase implementation complexity of the receiver. A direct implementation of these multiuser algorithms in current generation DSP-based base-station receivers fails to meet third generation real-time requirements. Therefore only single user algorithms for data detection and channel estimation have been implemented in all current practical systems, such as IS-95. In a time varying channel the parameters change and hence the receiver updation becomes computationally impractical. The adaptive versions of the receivers [2] are capable of operating under dynamic channel conditions without requiring any parameters of the interfering users. The adaptive implementation necessitates the transmission of training sequence, which will consume a sizable portion of bandwidth allotted for data.

In the absence of training data, however, the derivation of a linear receiver with performance close to that of the MMSE solution pose a significant challenge. Of late, blind methods [3] for adapting the filter coefficients have appeared. In the blind scheme the receiver coefficients are adaptively determined without using training sequence. The receiver in this case needs only the signature code and timing of the desired user and in this respect it is same as CMF. In a multipath scenario the knowledge of the channel impulse response also is essential. In such situations channel estimation also can be performed in a blind adaptive manner. It is advantageous to integrate data detection and channel estimation to get a joint structure.

In this work we develop a joint, blind, adaptive, multiuser RAKE receiver for non-fading and fading multipath channels. The receiver structures proposed are decorrelating detector (also called decorrelator) and MMSE-like detector and the blind methods considered are constrained minimum output energy (CMOE) method using least mean square (LMS) algorithm. Decorrelating or MMSE filters corresponding to each path of the user of interest (UOI) is first determined in a blind, adaptive manner using MOE criterion. The received signals are then projected onto the subspace spanned by these filters to get the combined filter. The combined filter is not free from noise. The dominant eigen vector of the co-variance matrix of the projected signal is then computed to get the noise-free decorrelating or MMSE-like filter. The computation of the dominant eigen vector is also made adaptive using the rank-one, projection approximation subspace tracking by deflation (PASTd) algorithm. The performance of the proposed detector is then compared with existing methods both in fading and non-fading channel. An unbiased method for channel estimation also is proposed using results from the proposed work. We have also presented some miscellaneous works as the by-product of the main work.

1.2 OUTLINE OF THE THESIS

The thesis is organised as follows. Chapter 2 gives an overview of state-of-art of different wireless communication systems currently available. They include the second-generation CDMA/GSM systems and the third generation WCDMA systems. Chapter 3 is the literature survey on multiuser detection. It includes basic linear detectors and adaptive detectors. Blind versions of adaptive detectors like the CMOE and subspace detectors and an adaptive version of the subspace detector using subspace-tracking algorithm is also presented in this chapter. We also discuss inverse filtering criteria, minimum variance detectors and timing-free multiuser detectors. In Chapter 4 we discuss some preliminary works done to validate the performances of CMF, decorrelating and MMSE detectors. In MMSE we have simulated adaptive and non-adaptive versions. We also discuss the blind adaptive implementations. The implementation of minimum variance and subspace-based detectors is also discussed in chapter 4.

In chapter 5, we present the proposed detector. The formation, configuration of the detector is given there. An analysis, to show that the proposed detector is very close to a MMSE detector, is also given. In chapter 6, the performance of the proposed detector is compared with competing methods. First our method is compared with subspace method and RLS method for a single-path channel. Then we compare the performance of the proposed method with RLS method in a multipath scenario. In chapter 7 we analyse the performance of the proposed detector in fading channels. Both real and complex channel coefficients are taken care of. The performance in a Rayleigh fading channel is presented. In chapter 8, a new method for unbiased channel estimation is presented. In this case channel estimation is shown to be free from MAI and MPI. In chapter 9, we explain some miscellaneous topics, which are the by-products of our research on the main topic. Finally we conclude in chapter 10, with a suggestion for future work.

Chapter 2

OVERVIEW OF MOBILE COMMUNICATION SYSTEMS

2.1 INTRODUCTION

The design objective of early mobile radio systems was to achieve large coverage area by using a single, high power transmitter with antenna mounted on a tall tower. While this approach achieved very good coverage, it was not possible to reuse the frequencies in this system, because of interference. The cellular concept was a major breakthrough in solving the aforesaid problem. It offered very high capacity in a limited spectrum allocation without any technological changes. Cellular concept is a system level idea, which calls for replacing a single high power transmitter (large cell) with many low power transmitters (small cells). Each base station is allocated a portion of the total number of channels available to the entire system, and nearby base stations are assigned different groups of channels so that all the available channels are assigned to a relatively small number of neighbouring base stations. This arrangement can be repeated in the entire geographical area. All the base-stations are connected to public switched telephone network (PSTN) through the mobile switching centres (MSC).

While an analog cellular communication system uses frequency division multiple access (FDMA), a digital cellular system, in general uses either time division multiple access (TDMA) or code division multiple access (CDMA). The first analog system to be deployed was the American mobile phone system (AMPS).

This belongs to the first generation systems. The second generation, digital system using TDMA/FDMA was deployed in Germany in 1992. This is the well-known global system for mobile (GSM) and is a European version. The total number of channels in GSM is 124 with each channel occupying 200 KHz bandwidth and eight time slots are used within each 200 KHz channel. The uplink frequency is 935-960 MHz and downlink frequency is 890-915 MHz. The second generation, American version of the TDMA system is, IS-54/IS-136 and that of the CDMA system is, IS-95.

2.2 SECOND GENERATION CDMA SYSTEMS

The development of CDMA started in early 1989 after the North American TDMA standard was established. IS-95 was completed in 1993 and revised in 1995 as IS-95A. An up-banded version of IS-95 for the 1.9 GHz-personal communication system (PCS) frequency band was standardised in 1995. IS-95 is also a dual mode standard with AMPS systems. In designing the IS-95 system, the AMPS backward compatibility was taken into account. CDMA uses the idea of tolerating interference by spread spectrum modulation. The power control is a requirement in CDMA systems.

There are different modulation methods used in spread spectrum systems. They are direct sequence spread spectrum, frequency hopped spread spectrum and hybrid of these two. Direct sequence spread spectrum or direct sequence CDMA (DS-CDMA) is used for cellular communication. In CDMA each user is assigned a unique code sequence (spreading code), which is used to encode the information. The receiver, which knows the code sequence of the user, correlates the received signal with the code and recovers the information. This is possible because the cross-correlation between the code of the desired user and the codes of other users is zero or negligible. The multiple access capability of CDMA is achieved due to the spectral spreading of the transmitted signal. The ratio of the transmitted bandwidth to the information bandwidth is called the processing gain of the spread spectrum system. Some distinct properties of the spread spectrum signals over the narrow band signals are as follows.

- Multiple access capability: If multiple users transmit spread spectrum signal at the same time, the receiver will still be able to distinguish between the users, provided each user has unique code. Correlating the received signal with the code of the user of interest will de-spread only that user's information while other users' signal will remain spread over a large bandwidth.
- Protection against multiple-path interference: MPI will be rejected by the spread spectrum signal.

2.2.1 DS-CDMA systems

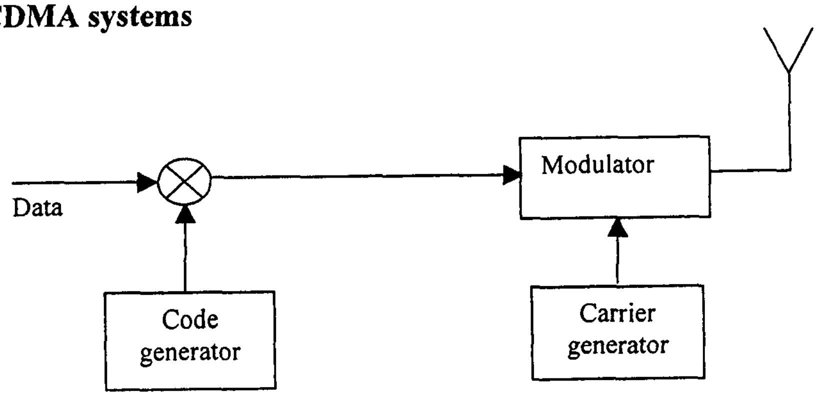

Fig. 2.1 DS-CDMA Transmitter

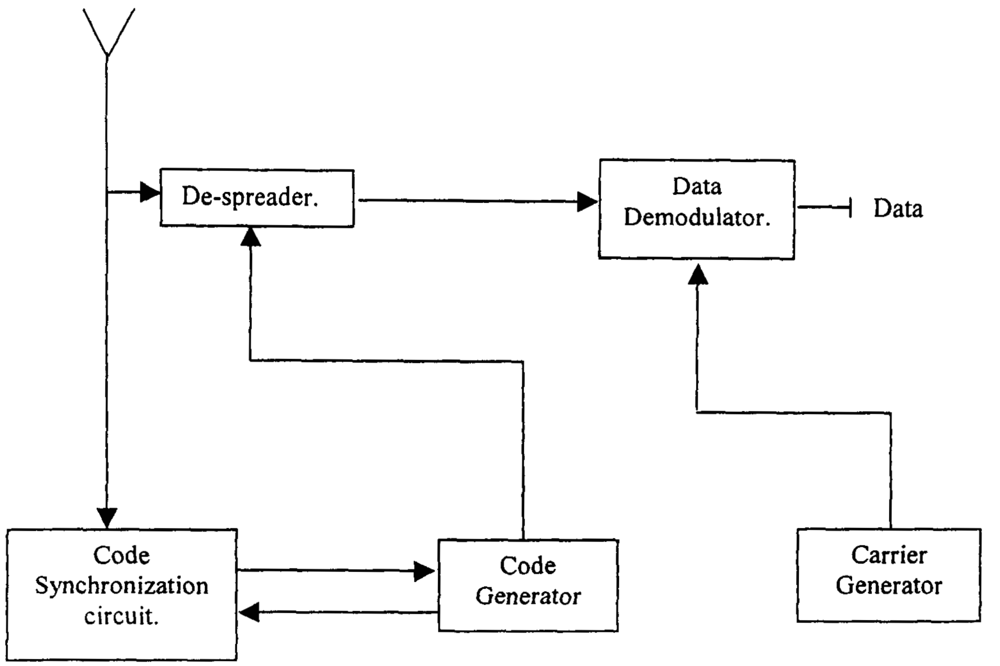

Fig. 2.2 DS-CDMA Receiver

The transmitter and receiver of a DS-CDMA system is shown in Fig.2.1 and Fig.2.2 respectively whose blocks are self-explanatory.

2.2.2 Elements of DS-CDMA (IS-95)

Reverse CDMA channel signals

The channel used for mobile station to base station communication is called reverse channel (uplink). The reverse CDMA channel is composed of access channels and reverse traffic channels. Since mobile station does not establish a system time at the base station, the reverse channel signal received at the base station cannot use coherent detection. The modulation used for the reverse channel is 64-ary orthogonal modulation [4].

Direct sequence spreading

Prior to transmission, the reverse traffic channel and the access channel are direct sequence spread by the long code at point F as shown in Fig. 2.3. The long code is periodic with a period equal to 2^{42}-1.

Quadrature spreading

The spread polynomials of in-phase (I) and quadrature-phase (Q) channel pilot PN sequences with period 2^{15}-1 are,

$$P_I(x) = x^{15} + x^{13} + x^9 + x^8 + x^7 + x^5 + 1 \tag{2.1}$$

$$P_Q(x) = x^{15} + x^{12} + x^{11} + x^{10} + x^6 + x^5 + x^4 + x^3 + 1 \tag{2.2}$$

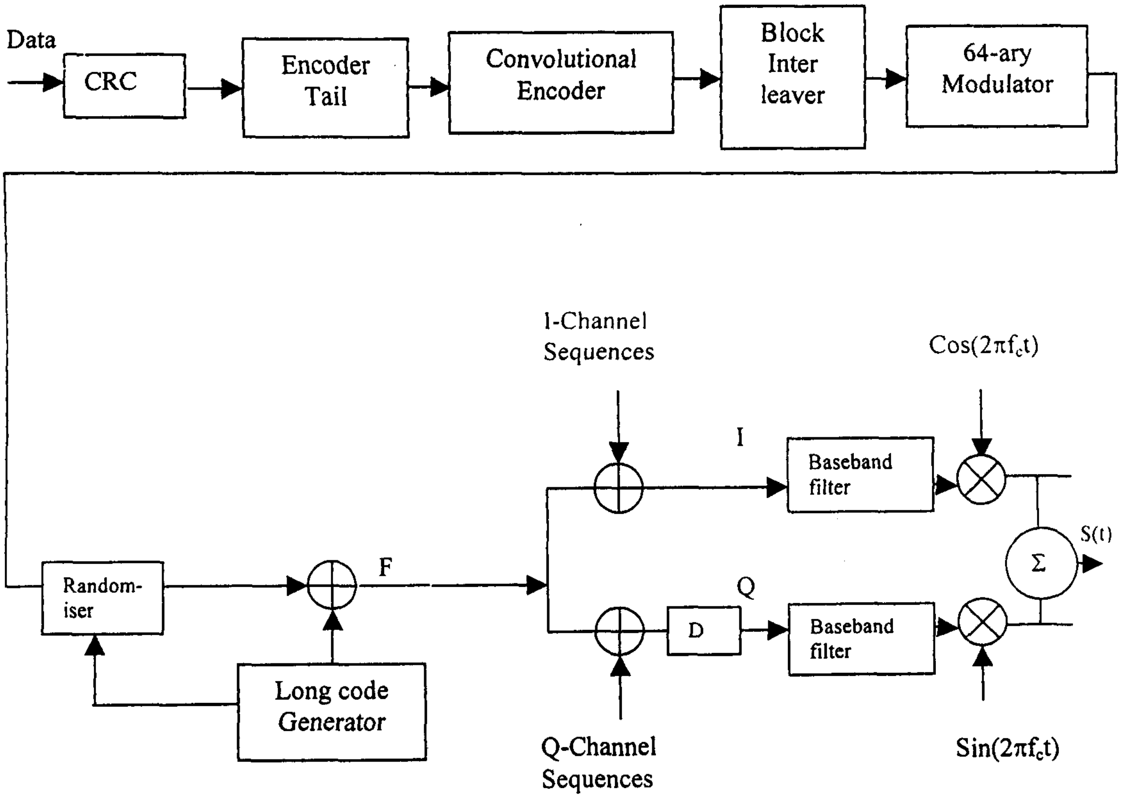

Fig 2. 3 Reverse CDMA channel structure

Orthogonal modulation for reverse channel

The 64-ary Walsh codes consist of 64 codes, each with 64 bits long. The codes are orthogonal to each other. Every six symbol, interpreting each Walsh code of 64 chips, is sent.

Forward CDMA channel signals

The channel used for base station to mobile station communication is called forward channel (down-link). The forward CDMA channels consist of the pilot channels, paging channels and forward traffic channels, each of which is orthogonally spread by one of 64 Walsh function codes and is then spread by a quadrature pair of PN sequences at a fixed chip rate of 1.2288 Mcps. The structure of the forward channel is given in Fig. 2.4. The forward traffic channel supports variable data rate operating at 9600, 4800, 2400 or 1200 bps.

PN sequence offset

A pilot channel is transmitted all times on the first Walsh function (W_0) by the base station. Pilot PN sequence offset is used for identifying each base station.

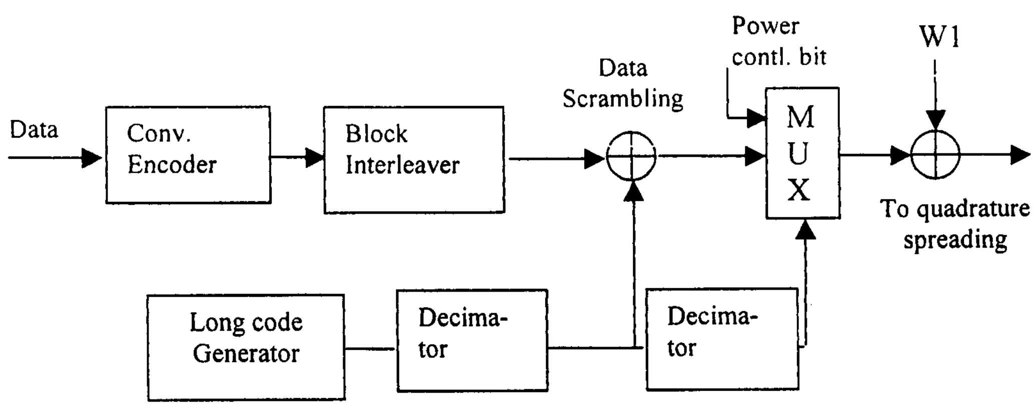

Fig 2.4 Forward CDMA channel structure

Power control

The requirement for power control is the most serious negative point in the up-link of a DS-CDMA system. The power control problem arises because of multiple access interference. All users use the same bandwidth at the same time and therefore users interfere with one another. Due to the propagation loss, the signal received by the base station from a user terminal in the vicinity of the base station, will be stronger than the signal received by the base station from a user terminal located at the cell boundary. Hence distant intended users will be dominated by nearby interfering users. This effect is called near-far effect. To achieve considerable capacity, all signals irrespective of distance, should arrive at the base station with same mean power. The solution to this problem is power control. There exist two types of power control methods, viz., open loop and close loop. In contrast to the uplink, in the downlink all signals propagate through the same channel and thus are received by mobile station with equal power. Therefore, power control is not mandatory in the downlink

Hand-over

Hand-over or hand-off is performed when a mobile moves from one cell to another. Neighbouring cells of a cellular system using either FDMA or TDMA do not use the frequencies used by the reference cell. Usually a mobile station performs hand-over, when the signal strength of the neighbouring cell exceeds the signal strength of the reference cell by a given threshold. This is called hard hand-over.

However in soft hand-over mobile stations are connected to either two or more base stations. A mobile station enters soft hand-over state when the signal strength of the neighbouring cell exceeds a certain threshold, but it is still below the current base station's strength. Because of processing gain, frequency reuse factor of one can be used in CDMA and the signal structure of CDMA is well suited for the implementation of soft hand over. This is because in the uplink, two or more base stations can receive the same signal and in the downlink, the mobile station can coherently combine the signals from different base stations since it sees them as just additional multiple path component.

RAKE Receiver

A DS-CDMA signal is well suited to the multiple-path channel. In a multiple-path channel, the original transmitted signal is reflected due to obstacles, and the receiver receives several copies of the signal with different delays. If the signal arrives more than one chip apart from each other, then the receiver can resolve them. Actually, from each signal's point of view other multipath signals can be regarded as interference, and they are suppressed by the processing gain. However a further benefit is obtained if the resolved multipath signals are combined using RAKE receiver.

Multiuser detection

The current CDMA receivers are based on the matched filter principle, which treats other user's signal as white noise. Multiuser detection (MUD) provides means of reducing the effect of MAI, and hence increases the system capacity. In addition to capacity improvement, MUD eliminates the near far problem.

2.3 THIRD GENERATION SYSTEMS

In the international telecommunication union (ITU), third generation networks are called, international mobile telecommunication system (IMTS) and in Europe, universal mobile telecommunication system (UMTS). Both these systems go under the ITU name of IMT-2000 [5]. IMT-2000 will provide a multitude of services especially multi-media and high bit rate packet data. Wideband CDMA has emerged as a mainstream air interface solution for third generation networks. The wide band CDMA proposal in Europe and in Japan is called WCDMA and in United States, cdma 2000.

The main objectives for the IMT-2000 air interface can be summarised as follows,

- Full coverage and mobility for 144 Kbps, preferably at 384 Kbps.
- Limited coverage and mobility for 2 Mbps.
- High spectrum efficiency compared to existing systems.
- High flexibility to introduce new services.

2.3.1 WCDMA structure

The main differences between WCDMA and cdma 2000 [1,6] are in chip rate, down link channel structure, and network synchronisation. cdma 2000 uses a chip rate of 3.6864 Mcps for the 5 MHz band allocation with direct spread down-link, and 1.2288 Mcps chip rate for a multi-carrier down link. WCDMA uses direct spreading with chip rate of 4.096 Mcps. Similar to IS-95, the spreading codes of cdma 2000 are generated using different phase shifts of the same sequence. This is possible because of the synchronous network operation. Since WCDMA has asynchronous network, different phase shifts of the same code cannot be used for cell and user separation.

The nominal bandwidth of all third generation proposals is 5MHz. There are several reasons for using this bandwidth. First, data rates of 144 and 384 Kbps are available within a bandwidth of 5 MHz. Secondly, lack of spectrum calls for reasonably small minimum spectrum allocation, especially if the system has to be deployed within the existing frequency bands already occupied by the second-generation system. Thirdly, large bandwidth can resolve more multiple paths than a narrower bandwidth thus increasing diversity and performance. Large bandwidths of

10, 15 and 20 MHz have been proposed to support highest data rates more efficiently.

Uplink physical channels

There are two dedicated channels and one common channel on the uplink [1,6]. User data is transmitted on the dedicated physical data channel (DPDCH) and control information is transmitted on the dedicated physical control channel (DPCCH). The random access channel is a common access channel. Each DPDCH frame on a single code carries $16x2^k$ Kbps, corresponding to a spreading factor of $256/2^k$ with 4.096 Mcps chip rate (with k an integer which varies from 0 to 6). The DPCCH channel is needed to transmit pilot symbols for coherent reception, power control signalling bits and rate information for rate detection.

Downlink physical channels

In the downlink there are three common physical channels. The primary and secondary common control physical channels (CCPCH) carry, the downlink common control logical channels. The synchronous channel (SCH) provides timing information and is used for hand over measurements by the mobile station. The dedicated channels DPDCH and DPCCH are time division multiplexed.

Spreading

The WCDMA scheme employs long spreading codes for cell separation in the downlink and user separation in the uplink. In the downlink, Gold codes of length 2^{18} are used, but they are truncated to form a cycle of 10 ms frame. The total number of available scrambling codes is 512, divided into 32 code groups with 16 codes in each group to facilitate a fast cell search procedure. In the uplink, either short or long spreading codes are used. The short codes are used to ease the implementation of multiuser receiver techniques. For channelization orthogonal codes are used.

2.3.2 cdma 2000

Uplink physical channels

On the uplink, there are four different dedicated channels [6]. The fundamental and supplemental channels carry user data. A dedicated control channel, with a frame length 5 or 20 ms carries control information such as measurement data and a pilot channel is used as a reference signal for coherent detection.

Downlink physical channels

Downlink has three different dedicated channels. Similar to uplink, the fundamental and supplemental channels carry user data and the dedicated control channels carry control messages. The mobile station uses the synchronisation channel, to acquire initial time synchronisation. One or more paging channels are used for paging the mobiles. The pilot channel provides a reference signal for coherent detection, cell acquisition and hand over.

Spreading

On the down link the cell separation for cdma 2000 is performed by two maximal-length sequences (m-sequences) of length 2^{15}, one for the in-phase (I) channel and one for the quadrature (Q) channel which are phase shifted by PN offset for different cells. Thus during the cell search process only these sequences need be searched. In the uplink, user separation is performed by different phase shifts of m-sequences of length 2^{41}. The channel separation is performed using variable spreading factor Walsh sequences, which are orthogonal to each other.

2.4 CONCLUSION

An overview of the terrestrial radio transmission technology of second generation (2G) and third generation (3G) radio systems is presented. Despite the call for a common global standard, there are some differences in the proposed technologies, notably in chip-rate and inter cell operation. These differences are partly due to the existing 2G infrastructures already in use all over the world, specifically due to the heritage of GSM and IS-95 systems. Huge capital has been invested in these 2G mobile systems. Due to the diversified nature of these 2G systems, it is not easy task to reach a common 3G standard that can maintain perfect backward compatibility.

Chapter 3

LITERATURE SURVEY

3.1 INTRODUCTION

In this chapter different multiuser detection schemes available in literature are surveyed. In 1984, Verdu proposed and analysed [7,8] the optimal multiuser detector and the maximum likelihood sequence estimator (MLSE), which unfortunately is too complex for practical implementations since its complexity grows exponentially as a function of the number of users. However, Verdu's work inspired researchers to find sub-optimal multiuser detectors.

The sub-optimal receivers can be divided in to two main categories, viz., linear detectors which perform interference suppression, and non-linear detectors which perform interference cancellation. Linear detectors apply a linear transformation onto the outputs of the matched filters that are trying to remove MAI. Examples of linear detectors are de-correlator and linear minimum mean-squared error (LMMSE) detectors. In the interference cancellation scheme, MAI is first estimated and then subtracted from the received signal. Parallel interference cancellation (PIC) and serial interference cancellation (SIC) are examples of interference cancellation. Different types of multiuser detectors are shown in Fig. 3.1.

In section 2, we describe two methods of forming linear detectors-the batch mode and adaptive mode. In the batch mode the detector is formed from some known parameters or from a batch of received symbols in a one-time fashion. In the adaptive mode the detector is updated in an adaptive manner on a symbol-by-symbol basis.

The adaptive detector can be implemented either by using training sequences or by using blind techniques. The adaptive laws used are LMS or RLS algorithms. Blind adaptive detectors are subsequently presented. In a multipath channel the multiuser filtering can take place either after multipath combining or prior to it. In this connection we present pre-combining and post-combining type of detectors in a multipath scenario. In section 3, we introduce the widely used subspace techniques for data detection and channel estimation. It can be shown that decorrelating or MMSE detectors can be obtained blindly using subspace techniques. Both adaptive and non-adaptive versions of data detection and channel estimation are presented under the subspace category. The use of inverse filtering criterion and minimum variance criterion for blind data detection in a multipath scenario is described in section 4 and 5 respectively. A timing-free blind multiuser detector is presented in section 6, which requires only the signature code of the desired user for data detection.

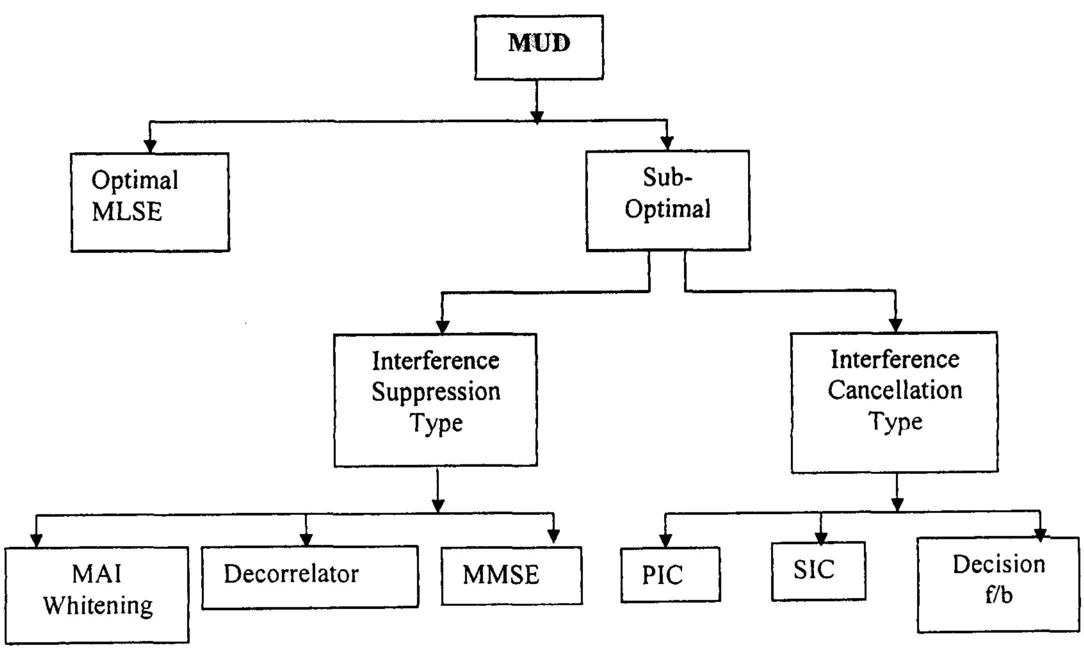

Fig. 3.1 Multiuser detectors

3.2 LINEAR DETECTORS

The decorrelator, also called zero-forcing detector proposed by Lupas & Verdu [7], multiplies the matched filter outputs by the inverse of the cross correlation matrix. An advantage of this detector is that the received signal amplitudes do not have to be known. On the other hand the noise also is filtered with inverse matrix and hence increases noise power. Since the decorrelator is a sequence detector the detection process cannot be started until the whole transmitted sequence is received at the receiver, and hence results in some delay. In the case of three users and single path propagation, the output of the bank of correlators represented in the vector form can be written [9] as,

$$\mathbf{y} = \mathbf{R_c A b + n}, \tag{3.1}$$

where, the normalized crosscorrelation matrix,

$$\mathbf{R_c} = \begin{bmatrix} 1 & \rho_{12} & \rho_{13} \\ \rho_{21} & 1 & \rho_{23} \\ \rho_{31} & \rho_{32} & 1 \end{bmatrix}$$

and **A,b,n** and ρ_{ij} represent received amplitudes of users in matrix form, transmitted data of the users in vector form, noise vector and the normalized cross correlation between the codes of *i*th and *j*th users, respectively. The inverse of $\mathbf{R_c}$ is multiplied with correlator filter outputs giving the estimated bits in vector form as

$$\hat{\mathbf{b}} = \mathrm{sgn}(\mathbf{R}_c^{-1}\mathbf{y}) = \mathrm{sgn}(\mathbf{Ab} + \mathbf{R}_c^{-1}\mathbf{n}) \tag{3.2}$$

It is to be noted here, that the code assignments should be done carefully to ensure that the inverse of the correlation matrix exists. Another linear detector is the linear minimum mean squared-error (LMMSE) detector, which does not enhance noise. This detector is based on the MMSE criterion. It performs a transformation that minimises the mean square error of the actual signal and received signal. The bit estimate in this case is given [9] by

$$\hat{\mathbf{b}} = \mathrm{sgn}([\mathbf{R}_c + \sigma^2 \mathbf{A}^{-2}]^{-1}\mathbf{y}) \tag{3.3}$$

where, σ^2 is the noise variance. Due to the fact that this detector considers and makes up for both noise and MAI, it has better BER performance than the decorrelator.

3.2.1 Adaptive MMSE receiver

The linear receiver defined by the transformation, $\mathbf{T} = [\mathbf{R}_c + \sigma^2 \mathbf{A}^{-2}]^{-1}\mathrm{y}$ in the previous section would require knowledge of $\mathbf{R}_c$ and a bank of matched filters. Thus it appears to suffer the problem of large assumed knowledge in common with many multiuser receivers. Repeated matrix multiplication would be necessary if the channel is non-stationary, and so the technique would be computationally expensive. The advantage of MMSE receiver is the ease with which it can be implemented adaptively.

It would be desirable to obtain a linear multiuser detector that would not only eliminate the need for on line computation of its impulse response, but it would also eliminate the need to know the cross correlations, or in general the signature waveforms of the interfering users. It can be shown that such goal can be accomplished with an adaptive implementation of the MMSE receiver, which learns the desired filter impulse response from the received training sequence. The receiver uses an adaptive law to adjust its linear transformations while training sequences are sent. If the cross correlations and amplitudes vary over time, training sequence can be sent periodically to readjust the receiver. The use of LMS algorithm for adaptation is explained now.

Least mean square algorithm

The LMS algorithm approximates the method of steepest descent. It operates by taking small steps on the quadratic error performance surface in the direction of negative gradient. Fig. 3.2 shows the structure of an adaptive MMSE receiver for a single user, realized by direct processing of sampled received signal. This can be implemented by using simple tapped delay line filter with appropriate tap update mechanism. Accurate synchronisation and multiuser processing stages are unnecessary. In the figure, T_c is the chip interval, N is the length of the code, **r** is the received signal and $\hat{b}_k$ is the output data, $\{m_k(i)\}_{i=1}^{N}$ are the elements of the filter vector $\mathbf{m}_k$.

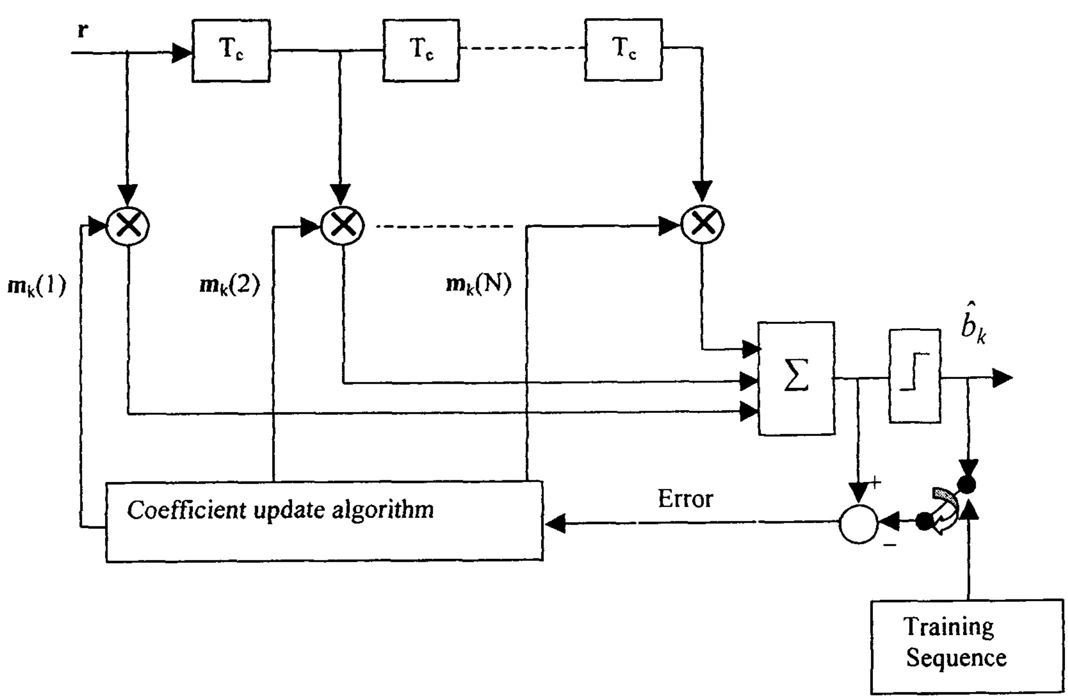

Fig. 3.2 Single user adaptive MMSE receiver

3.2.2 Blind adaptive MMSE receiver

A major impediment in the use of the adaptive MMSE receiver is the requirement for training sequence. Time is spent in training the receiver rather than sending useful data. Blind adaptive techniques can eliminate the need for training sequence. Two algorithms in this connection are presented now.

3.2.2.1 RLS algorithm

Many authors have considered application of the RLS algorithm to the linear MMSE receiver. It provides much more rapid convergence than the LMS algorithm. Furthermore the convergence rate is independent of the eigen value spread of the correlation matrix. A major impediment in using the RLS algorithm is its computational complexity.

The exponentially windowed RLS algorithm selects the weight vector $\mathbf{m}(n)$ to minimize the sum of exponentially weighted output energy as shown,

$$\text{Minimize } \sum_{i=1}^{n} \lambda^{n-i}[\mathbf{m}^{T}(n)\mathbf{r}(i)]^{2} \text{ subject to } \mathbf{s}^{T}\mathbf{m}(n) = 1 \tag{3.4}$$

where $\mathbf{s}$ is the signature code of the desired user, $\mathbf{r}(i)$ the received sequence and $0 < \lambda < 1$ is the forgetting factor which is used to ensure that data in the distant past are forgotten in order to provide the tracking capability, in a non-stationary environment. The solution to this constrained optimization problem is given by

$$\mathbf{m}(n) = \frac{1}{\mathbf{s}^{T}\mathbf{R}^{-1}(n)\mathbf{s}}\mathbf{R}^{-1}(n)\mathbf{s}, \text{ where } \mathbf{R}(n) \triangleq \sum_{i=1}^{n} \lambda^{n-i}\mathbf{r}(i)\mathbf{r}^{T}(i) \tag{3.5}$$

A recursive procedure with complexity $O(N^2)$ for updating $\mathbf{m}(n)$ can be obtained as follows

$$\mathbf{k}(n) \triangleq \frac{\mathbf{R}^{-1}(n-1)\mathbf{r}(n)}{\lambda + \mathbf{r}^T(n)\mathbf{R}^{-1}(n)\mathbf{r}(n)} \tag{3.6}$$

$$\mathbf{h}(n) \triangleq \mathbf{R}^{-1}(n)\mathbf{s} = \frac{1}{\lambda}[\mathbf{h}(n-1) - \mathbf{k}(n)\mathbf{r}^T(n)\mathbf{h}(n-1)] \tag{3.7}$$

$$\mathbf{m}(n) = \frac{1}{\mathbf{s}^T\mathbf{h}(n)}\mathbf{h}(n) \tag{3.8}$$

$$\mathbf{R}^{-1}(n) = \frac{1}{\lambda}[\mathbf{R}^{-1}(n-1) - \mathbf{k}(n)\mathbf{r}^T(n)\mathbf{R}^{-1}(n-1)] \tag{3.9}$$

It has been shown in [26] that the steady state SIR of the above algorithm is given by

$$\mathrm{SIR}^{\infty} = \mathrm{SIR}^{*}/(1 + \mathrm{d} + \mathrm{d}.\mathrm{SIR}^{*}), \tag{3.10}$$

where SIR^* is the optimal SIR value and $\mathrm{d} \triangleq (\frac{1-\lambda}{2\lambda})N$. Hence the performance of the algorithm is upper bounded by 1/d when 1/d << SIR^*.

3.2.2.2 LMS algorithm

An adaptive algorithm for a blind detector based on constrained minimum output energy (CMOE) principle is presented by Verdu [9]. The approach, adopted to self-tune the detector, is based on the stochastic gradient descent of the convex penalty function. In this case the penalty function is the output variance, where as mean square-error is the penalty function in the case of training-data based (data-aided) MMSE receiver. The output variance is minimised with respect to the component orthogonal to the desired user's signature waveform. A linear multi-user detector for user 1 is characterised by a vector $\mathbf{m}_1$, such that,

$$\hat{b}_1 = \mathrm{sgn}\,(\langle \mathbf{r}, \mathbf{m}_1 \rangle) \tag{3.11}$$

where, $\mathbf{r}$ is the received signal. Let us introduce a canonical representation for $\mathbf{m}_1$ as

$$\mathbf{m}_1 = \mathbf{s}_1 + \mathbf{x}_1 \tag{3.12}$$

where, $\mathbf{s}_1$ is the signature waveform of user 1, and $\mathbf{x}_1$ is such that $< \mathbf{s}_1, \mathbf{x}_1 > = 0$. The representation in (3.12) is canonical in that every linear multiuser detector for user 1 can be expressed in that form. This is because the set of signals $\mathbf{m}_1$ that can be written as above satisfy $< \mathbf{s}_1, \mathbf{m}_1 > = \|\mathbf{s}_1\|^2 = 1$ and the decision in (3.11) is invariant to positive scaling.

In order to apply the gradient descent algorithm to the above penalty function, we must take into account that, at every iteration, $\mathbf{x}_1(n)$ must be orthogonal to $\mathbf{s}_1$, because we are following (on the average) the steepest descent line along the subspace orthogonal to $\mathbf{s}_1$. On projecting the unconstrained gradient on that subspace results, in the desired steepest descent line. To check this, simply note that the unconstrained gradient can be decomposed as the sum of its projections along $\mathbf{s}_1$ and its orthogonal subspace; steepest unconstrained descent requires steepest descent along each of these directions. Therefore, let us first take the unconstrained gradient of

$$\mathrm{MOE}\,(\mathbf{x}_1) = E\,[(< \mathbf{r}, \mathbf{s}_1 + \mathbf{x}_1 >)^2] \tag{3.13}$$

which lies in the same direction as the observed signal:

$$\nabla\, \mathrm{MOE} = 2 < \mathbf{r}, \mathbf{s}_1 + \mathbf{x}_1 > \mathbf{r} \tag{3.14}$$

The component orthogonal to $\mathbf{s}_1$ is a scaled version of the component of $\mathbf{r}$ orthogonal to $\mathbf{s}_1$:

$$\mathbf{r} - <\mathbf{r}, \mathbf{s}_1> \mathbf{s}_1.$$

Therefore the projected gradient (orthogonal to $\mathbf{s}_1$) is

$$2 <\mathbf{r}, \mathbf{s}_1 + \mathbf{x}_1> [\mathbf{r} - <\mathbf{r}, \mathbf{s}_1> \mathbf{s}_1] \tag{3.15}$$

The adaptive algorithm updating proceeds at the data rate. Let us denote the responses of the matched filters for $\mathbf{s}_1$ and $\mathbf{s}_1+\mathbf{x}_1[n-1]$, respectively by,

$$z_{MF}[n] = <\mathbf{r}[n], \mathbf{s}_1> \tag{3.16}$$

$$z[n] = <\mathbf{r}[n], \mathbf{s}_1+\mathbf{x}_1[n-1]> \tag{3.17}$$

Stochastic gradient adaptation rule is then,

$$\mathbf{x}_1[n] = \mathbf{x}_1[n-1] - \mu\, z[n](\mathbf{r}[n]-Z_{MF}[n]\mathbf{s}_1) \tag{3.18}$$

Remarkably, the above adaptive algorithm converges to the linear MMSE detector using no more information than the conventional matched filter, namely, the desired user's signature waveform and its timings. The process is depicted in Fig. 3.3. In the figure, T is the symbol delay and μ is the step-size parameter.

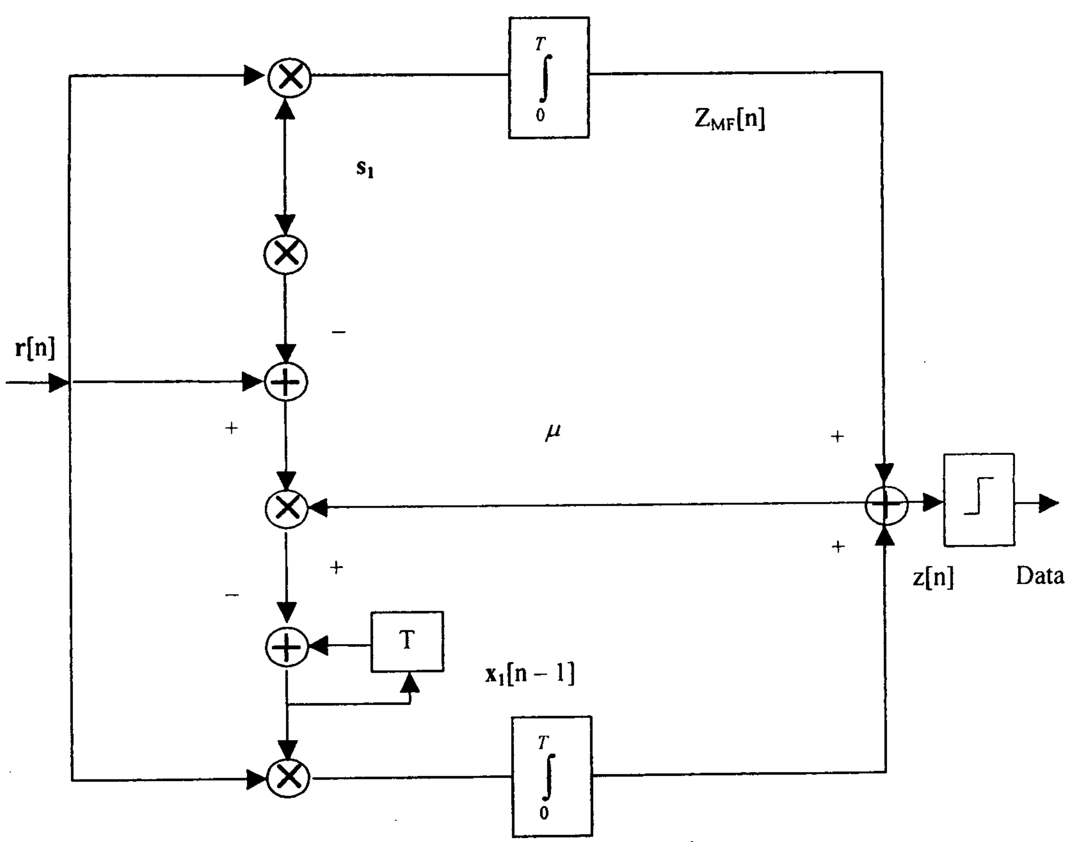

Fig. 3.3 Blind adaptive multiuser detector

3.2.3 LMMSE RAKE receiver

There are two approaches [10], which may be employed for linear MMSE detection in multipath channels. Multiuser filtering can take place either after multipath combining or prior to it. In other words, the multiuser receiver can be either post-combining interference suppression type of receiver as shown in Fig. 3.4 or a pre-combining interference type of receiver as shown in Fig. 3.5. Performance differences of two structures in known fixed channels have been compared in [11].

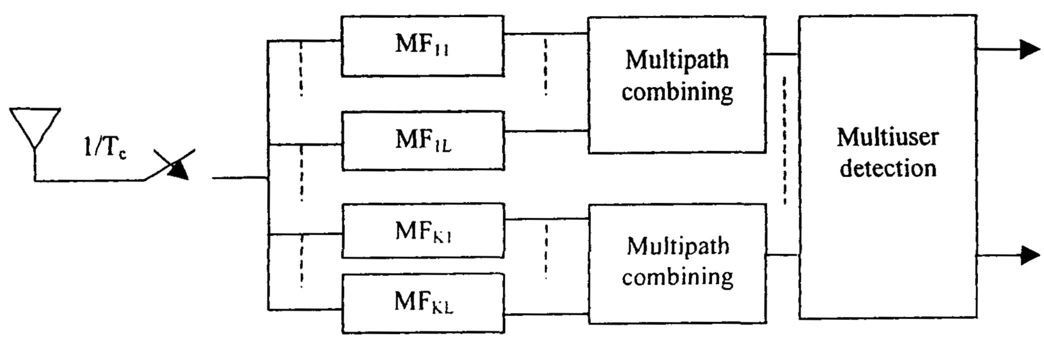

Fig. 3.4. Post-combining Multiuser receiver structure

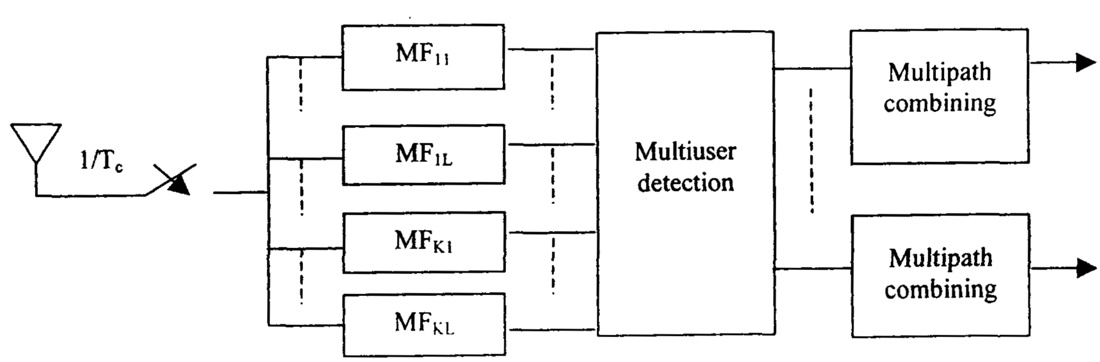

Fig.3.5 Precombining multiuser receiver

The results show that the order of multipath combining and interference suppression does not give a significant impact on the BER performance of the detector when the product of the number of users (K) and the number of multipath components (L) are relatively low. As the product, KL becomes large, the cross-correlation matrix of users' signature sequences becomes ill conditioned. In such a case, multipath combining prior to interference suppression usually yields stable matrix inversion and robust performance. However, multipath combining prior to interference suppression makes channel estimation more difficult since multiuser detector depends on the channel estimates, which cannot be estimated at the output of the detector in that case. Therefore practical implementations of multiuser receivers have to perform first interference suppression and subsequently, channel estimation. Such receivers also have the advantage that the detector does not depend on the fading channel state.

A post-combining LMMSE receiver minimises the cost function $E\{|b-\hat{b}|^2\}$ element wise, where $\hat{b} = \mathbf{m}^H\mathbf{r}$, $\mathbf{m}$ is the receiver filter and $\mathbf{r}$ is the received vector. It can be seen that post-combining LMMSE receiver in fading channels depends on the complex channel coefficients of all users and all paths. If the channel is changing rapidly, the optimal LMMSE receiver changes continuously. Thus, the adaptive versions of the LMMSE receivers have increasing convergence problems as the fading rate increases.

The dependence on the fading channel can be removed by applying a pre-combining interference suppression type of receiver. This can be accomplished by minimising each element of $E\left\{\left|d - \hat{d}\right|^2\right\}$ where d = hab is the product of the channel coefficients h, user amplitudes a, data b and $\hat{d} = \mathbf{m}^T\mathbf{r}$, is the estimated value of d. As can be seen, the pre-combining receiver no longer depends on the instantaneous values of the complex channel coefficients, but on the average power profiles of the channel. The adaptation requirements are now significantly milder, and the receiver can be made adaptive even in relatively fast fading channels. Since interference is separately suppressed in each multi-path component before multi-path combining, the pre-combining LMMSE receiver has the same structure as the conventional RAKE receiver. Hence the pre-combining LMMSE is called an LMMSE-RAKE receiver. Pre-combining LMMSE receiver can be made by using decision feedback of a conventional RAKE receiver [12] or by using blind adaptive algorithms [13]. The adaptive LMMSE receiver is actually an adaptive RAKE receiver where each receiver branch is adapted independently to suppress MAI. The general block diagram of such a receiver [14] is shown in Fig. 3.6. Here the filter weights are calculated iteratively by using stochastic gradient algorithm, such as LMS algorithm.

If the adaptive receiver is used aside of a conventional RAKE receiver, it is convenient to decompose the filter vector to fixed and adaptive components

$$\mathbf{m}_{kl}^{(n)} = \mathbf{s}_{kl} + \mathbf{x}_{kl}^{(n)} \tag{3.19}$$

where, $\mathbf{s}_{kl}$ is the fixed spreading sequence of the kth user with delay τ_{kl} and $\mathbf{x}_{kl}^{(n)}$ is the adaptive filter component. If the standard LMS algorithm is used for adapting the filter, the updates for the adaptive component can be written as

$$\mathbf{x}_{k,l}^{(n)} = \mathbf{x}_{k,l}^{(n-1)} + 2\mu_{k,l}^{(n)} e_{k,l}^{*(n)} \mathbf{r}^{(n)} \tag{3.20}$$

where, $\mu_{k,l}^{(n)}$ is the time-variant step-size parameter, which controls the rate of convergence of the algorithm. The actual value of the step-size is very crucial for the adaptive standard LMMSE receiver when used in fading channels. Since this LMMSE does not need to track the fading channel coefficients, the step-size can be set more freely. However, when using an imperfect reference signal obtained from the channel estimates and the data decisions of a conventional RAKE receiver, the step-size should be small enough in order to average the impact of channel estimation and the decision errors in the LMS algorithm. The output of the lth receiver branch can now be written as $y_{kl}^{(n)} = \mathbf{m}_{kl}^{H(n)}\mathbf{r}^{(n)}$.

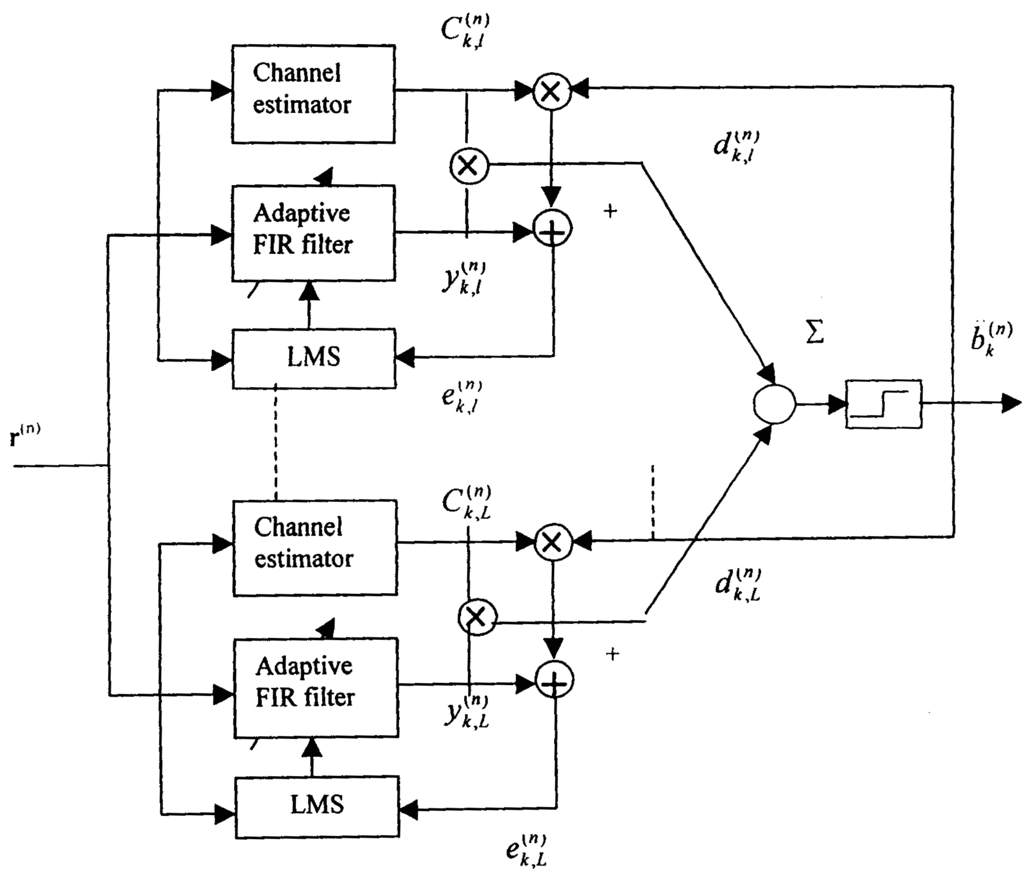

Fig. 3.6 General block diagram of an adaptive LMMSE receiver (Pre-combining type)

The error signals, $e_{k,l}^{(n)} = d_{k,l}^{(n)} - y_{k,l}^{(n)}$, produced by the difference between the filter outputs and the reference signals, are used to update the filter weights. Either known (data aided) or estimated data (decision directed) symbols are used as reference signals in the standard adaptive LMMSE receivers. The product of the estimated channel coefficients and data symbols is the reference signal in the modified LMMSE receiver ($d_{k,l}^{(n)} = \hat{h}_{k,l}^{(n)} b_k^{(n)}$ or $d_{k,l}^{(n)} = \hat{h}_{k,l}^{(n)} \hat{b}_{k,l}^{(n)}$) respectively. The data decisions produced initially by a conventional RAKE receiver are often reliable enough for adapting the receiver.

It is clear that, channel estimator performance affects significantly the convergence of the adaptive receiver. If the system provides a modulated pilot channel, the channel can be estimated accurately from the pilot. The most trivial way to estimate the channel coefficients from the pilot channel is to filter the pilot channel correlator outputs with a moving average filter. In fast fading channels when averaging interval must be rather short, a near-far resistant channel estimator, like one based on the LMMSE criterion could be used to provide reliable channel estimates.

3.3 SUBSPACE METHODS

Subspace methods can be used for multiuser detection and channel estimation. Let us discuss the signal model used before we actually start subspace methods. Consider a base-band synchronous direct sequence CDMA system with K active users. The received signals can be modeled as [15],

$$r(t) = s(t) + \sigma n(t) \tag{3.21}$$

where $n(t)$ is white, Gaussian noise with unit power spectral density, σ^2 is the variance of noise and $s(t)$ is the superposition of the data signals of K users, given by

$$s(t) = \Sigma_{k=1}^{K} A_k \Sigma_{n=-M}^{M} b_k(n) s_k(t - nT - \tau_k) \tag{3.22}$$

where $2M+1$ is the number of data symbols per user per frame, T is the symbol interval and $A_k, \tau_k, \{b_k(n); n = 0, \pm 1, \ldots\ldots\ldots \pm M\}$ and $\{s_k(t); 0 \le t \le T\}$ denote respectively, the received amplitude, delay, symbol stream, and normalized signalling waveform of the *k*th user. For the DS-CDMA multiple access format, the user signalling waveform are of the form

$$s_k(t) = \Sigma_{j=1}^{N} \beta_j^k \varphi[t-(j-1)T_c], t \in [0,T] \tag{3.23}$$

where, N is the processing gain, $(\beta_1^k, \ldots\ldots\ldots\ldots\ldots \beta_N^k)$ is the signature sequence of $\pm 1s$ assigned to the *k*th *user*, $\varphi(t)$ is a normalized chip waveform of duration T_C, with $NT_C = T$.

In this work we restrict our attention to the synchronous CDMA, *in which*, $\tau_1 = \tau_2 = \ldots\ldots \tau_K = 0$. *It is then sufficient to consider* received signal during one symbol interval, and the received signal model becomes

$$r(t) = \Sigma_{k=1}^{K} A_k b_k s_k(t) + \sigma n(t), t \in [0,T] \tag{3.24}$$

At the receiver, chip matched filtering followed by chip rate sampling yields an N-vector of chip filter output samples, within a symbol interval T as shown,

$$\mathbf{r} = \Sigma_{k=1}^{K} A_k b_k \mathbf{s}_k + \sigma \mathbf{n} \tag{3.25}$$

where, $\mathbf{s}_k = 1/\sqrt{N}[\beta_1^k, \ldots\ldots\ldots\ldots\ldots \beta_N^k]^T$ is the normalized signature vector of the *k*th user, and **n** is a white Gaussian noise vector with mean zero and covariance matrix $\mathbf{I}_N$.

3.3.1 Channel estimation using subspace method

For a dispersive frequency selective channel the discrete counterpart of the effective signature waveform is given by [16]

$$\tilde{s}(i) = \sum_{r=1}^{N} s(r)h(i-r+1) \tag{3.26}$$

where , h(l) = Samples of the channel response; l =1.....L

$s(r)$ = Elements of the signature code; $r = 1 \ldots\ldots N$

N = Length of the signature code

L = Number of resolvable multiple paths

The above convolution can be represented as

$$\tilde{\mathbf{s}} = \begin{bmatrix} s(1) & & & \\ s(2) & s(1) & & \\ & & \vdots & \\ s(N) & & \cdots & s(1) \\ & s(N) & \cdots & s(2) \\ & & \vdots & \\ & & & s(N) \end{bmatrix} \mathbf{h} = \mathbf{S}\mathbf{h} \qquad (3.27)$$

The discrete version of the ISI free signature waveform is given by

$$\bar{\mathbf{s}} = \begin{bmatrix} s(L)\ldots\ldots\ldots\ldots\ldots\ldots\ldots s(1) \\ s(L+1)\ldots\ldots\ldots\ldots\ldots s(2) \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ s(N)\ldots\ldots\ldots s(N-L+1) \end{bmatrix} \mathbf{h} = \bar{\mathbf{S}}\mathbf{h} \qquad (3.28)$$

For a synchronous-CDMA (S-CDMA) system with K users, the ISI free data vector $\mathbf{x}(n)$ can be written as

$$\mathbf{x}(n) = \sum_{k=1}^{K} \gamma_k \bar{\mathbf{s}}_k b(n) \qquad (3.29)$$

where, the subscript k denotes the user index, γ_k is complex gain of the signal from the *k*th user, $b_k(n)$ denotes *n*th data of the *k*th user. Given M data vectors, we have

$$\mathbf{X} = [\mathbf{x}(1)\ \mathbf{x}(2)\ \ldots\ldots\ldots\ldots \mathbf{x}(M)] = [\gamma_1 \bar{\mathbf{s}}_1\ \gamma_2 \bar{\mathbf{s}}_2 \cdots \gamma_K \bar{\mathbf{s}}_K] \mathrm{x}\, \mathbf{B} \qquad (3.30)$$

Where, $$\mathbf{B} = \begin{bmatrix} b_1(1) & b_1(2) & \cdots & b_1(M) \\ b_2(1) & b_2(2) & \cdots & b_2(M) \\ \cdots & \cdots & \cdots & \cdots \\ b_K(1) & b_K(2) & \cdots & b_K(M) \end{bmatrix}$$

The general problem addressed here is the estimation of $\{\bar{s}_k\}$ or $\{\tilde{s}_k\}$ from **X** without the knowledge of **B**.

Given the data matrix as above a subspace decomposition can be performed on **X** by singular value decomposition (SVD) as shown below.

$$\mathbf{X} = \begin{pmatrix} \mathbf{U}_s & \mathbf{U}_o \end{pmatrix} \begin{pmatrix} \sum s & 0 \\ 0 & 0 \end{pmatrix} \begin{pmatrix} \mathbf{V}_S^H \\ \mathbf{V}_O^H \end{pmatrix} \tag{3.31}$$

where the vectors in **Us,** associated with K nonzero singular values , span the signal subspace while the vectors in **Uo,** associated with zero singular values , span orthogonal subspace which is the orthogonal complement of the signal subspace. Here $\sum s$ are the non-zero singular values and **V,** another unitary matrix. Hence we can write,

$$\mathbf{U}_O^H \bar{\mathbf{s}}_k = \mathbf{0} \tag{3.32}$$

Substituting for $\bar{\mathbf{s}}_k = \bar{\mathbf{S}}_k \mathbf{h}_k$, we get

$$\mathbf{U}_O^H \bar{\mathbf{s}}_k \mathbf{h}_k = 0, k = 1, \ldots\ldots K \tag{3.33}$$

The above equation along with the constraint, $\|\mathbf{h}_k\| = 1$, provides us with an efficient way to identify channel vector up to a phase ambiguity directly from the data matrix, i.e. by using this method the channel can be identified blindly.

3.3.2 Data detection using subspace method

The data detection also can be performed by singular value decomposition [3]. In the first method, the estimated channel parameters are used to get the composite signature waveform and the data detection is performed as done in a single-path channel. Here the received signal $\mathbf{r}$ is projected onto the signal subspace to get a K-vector,

$$\mathbf{z} = \mathbf{U_S}^H \mathbf{r}. \tag{3.34}$$

The desired user's composite signature waveform $\tilde{\mathbf{s}}_k$ is also projected on to the signal subspace to obtain,

$$\mathbf{p}_k = \mathbf{U_S}^H \tilde{\mathbf{s}}_k . \tag{3.35}$$

The projection of the linear detector on the signal subspace is then a vector $c_k \in R^K$ such that the data bit is demodulated as $\hat{b}_k = \mathrm{sgn}[\mathbf{c}_K^H \mathbf{z}]$.

The projection of the linear zero-forcing detector and that of the MMSE detector in the signal subspace are given respectively by

$$\mathbf{c}_k^d = \begin{bmatrix} \frac{1}{\lambda_1 - \sigma^2} & & \\ & \ddots & \\ & & \frac{1}{\lambda_K - \sigma^2} \end{bmatrix} \mathbf{p}_k \tag{3.36}$$

$$\mathbf{c}_k^m = \begin{bmatrix} \frac{1}{\lambda_1} & & \\ & \ddots & \\ & & \frac{1}{\lambda_K} \end{bmatrix} \mathbf{p}_k \tag{3.37}$$

where $\lambda_1 \ldots \lambda_K$ are the K largest eigen values of $\mathbf{R}=E\{\mathbf{rr}^T\}$ and σ^2 is the variance of noise.

In the second method, data of the desired user travelling different paths (multiple paths) can be separately detected and then combined using a RAKE receiver, provided the channel parameters are given [17].

3.3.3 Signal subspace tracking

It is seen from the previous section that the linear multiuser detectors are obtained as long as the signal subspace components are identified. The classic approach to subspace estimation is through batch eigenvalue decomposition (EVD) of the sample autocorrelation matrix, or batch singular value decomposition of (SVD) of the data matrix, which is computationally too expensive for adaptive applications. Modern subspace tracking algorithms are recursive in nature and update the subspace in a sample-by-sample fashion. Various subspace-tracking algorithms exist in literature. One recently proposed projection approximation subspace tracking by deflation (PASTd) algorithm [18] is reviewed below. The advantages of this algorithm include almost sure global convergence to the signal eigen vectors and eigen values and low computational complexity.

Let $\mathbf{r} \in R^N$ be a random vector with autocorrelation matrix $\mathbf{R} = E\{\mathbf{r}\mathbf{r}^T\}$. Consider the scalar function

$$J(\mathbf{W}) = E\{\|\mathbf{r}-\mathbf{W}\mathbf{W}^T\mathbf{r}\|^2\} \tag{3.38}$$

with matrix argument $\mathbf{W} \in R^{N\times r}$ $(r < N)$. It can be shown that,

- $\mathbf{W}$ is a stationary point of $J(\mathbf{W})$ if and only if $\mathbf{W} = \mathbf{U}_r\mathbf{Q}$, where $\mathbf{U}_r \in R^{N\times r}$ contains any r distinct eigen vectors of $\mathbf{R}$ and $\mathbf{Q} \in R^{r\times r}$ is any unitary matrix.
- All stationary points of $J(\mathbf{W})$ are saddle points except when $\mathbf{U}_r$ contains r dominant eigen vectors of $\mathbf{R}$. In that case, $J(\mathbf{W})$ attains the global minimum.

In applications, only sample vectors $\mathbf{r}(i)$ are available. Replacing (3.38) with the exponentially weighted sum yields,

$$J[\mathbf{W}(n)] = \sum_{i=1}^{n} \lambda^{n-i} \|\mathbf{r}(i)-\mathbf{W}(n)\mathbf{W}(n)^T\mathbf{r}(i)\|^2 \qquad (3.39)$$

Where, $0 < \lambda \leq 1$ is the forgetting factor. The key issue of the PASTd approach is to approximate $\mathbf{W}(n)^T\mathbf{r}(i)$ in (3.39), the unknown projection of $\mathbf{r}(i)$ onto the columns of $\mathbf{W}(n)$, by $\mathbf{y}(i) = \mathbf{W}(i-1)^H\mathbf{r}(i)$, which can be calculated for $1 \leq i \leq n$ at time n. This results in a modified cost function,

$$\bar{J}[\mathbf{W}(n)] = \sum_{i=1}^{n} \lambda^{n-i} \|\mathbf{r}(i)-\mathbf{W}(n)\mathbf{y}(i)\|^2. \qquad (3.40)$$

The recursive least squares algorithm can then be used to solve for $\mathbf{W}(n)$ that minimises the exponentially weighted least square criterion.

The PASTd algorithm for tracking the eigen values and eigen vectors of the signal subspace is based on the deflation technique and its basic idea is as follows. For r = 1 by minimising $\bar{J}(\mathbf{W}(n))$ in (3.40) the most dominant eigen vector is updated. Then the projection of the current data vector is removed from $\mathbf{r}(n)$ itself. Now the second most dominant eigen vector becomes the most dominant one in the updated data vector and it can be extracted similarly. This procedure is repeatedly applied until all the K eigen vectors are estimated sequentially. The algorithm for both rank and signal subspace tracking is summarised in Table 1 of [15]. The computational complexity of this algorithm is $(4K+3)N+O(K) \approx O(NK)$.

3.3.4 Blind adaptive estimation of multipath channel response

When the signal is transmitted over a multipath channel, at the receiver end, the effective signature waveform is the multichannel response to the original signature waveform. Suppose that K users are transmitting synchronously over a multipath channel, the number of resolvable paths for each user is $L = \lceil WT_m \rceil$ [15], where W is the signal bandwidth and T_m is the multipath spread of the channel. The impulse response of such a multipath channel for the *k*th user can be represented by a tapped delay line format:

$$h_k(t) = \Sigma_{l=1}^{L} h_{kl}\delta(t-(l-1)T_c) \tag{3.41}$$

Where $T_c = 1/W$, is the chip period and the coefficients h_{kl} are complex channel gains. The complex N-vector of chip matched filter output within a symbol interval is

$$\begin{aligned} \mathbf{r} &= \Sigma_{k=1}^{K} A_k b_k \Sigma_{l=1}^{L} h_{kl} \mathbf{s}_{kl} + \sigma\mathbf{n} \\ &= \Sigma_{k=1}^{K} A_k b_k \tilde{\mathbf{s}}_k + \sigma\mathbf{n} \end{aligned} \tag{3.42}$$

where, $\mathbf{s}_{kl}$ is the vector representation of the delayed user signature waveform, $s_k(t-(l-1)T_c)$ and $\tilde{\mathbf{s}}_k = \mathbf{S}_k\mathbf{h}_k$, is the received composite signature wave form of the *k*th user, with $\mathbf{S}_k = [\mathbf{s}_{k1}\mathbf{s}_{k2}\ldots\ldots\mathbf{s}_{kL}]$ and $\mathbf{h}_k = [h_{k1}\ h_{k2}\ldots\ldots h_{kL}]^T$. Suppose that the signal subspace is identified as, $\tilde{\mathbf{U}}_s = [\tilde{\mathbf{u}}_1\ \tilde{\mathbf{u}}_2\ldots\ldots\tilde{\mathbf{u}}_K]$. Since $\tilde{\mathbf{s}} \in \text{range}(\tilde{\mathbf{U}}_s)$ there exists $\mathbf{f}_1 \in C^K$ such that $\tilde{\mathbf{s}}_1 = \tilde{\mathbf{U}}_s\mathbf{f}_1$. On the other hand we also have $\tilde{\mathbf{s}}_1 = \mathbf{S}_1\mathbf{h}_1$. Therefore, $\tilde{\mathbf{s}}_1$ is given by one solution to the linear equation system $\mathbf{S}_1\mathbf{h}_1 = \tilde{\mathbf{U}}_s\mathbf{f}_1$. In the following we develop a recursive method for estimating multipath channel response $\mathbf{h}_1$ based on $\mathbf{S}_1$ and $\tilde{\mathbf{U}}_s$.

Since in practice $\widetilde{\mathbf{U}}_s$ is always a noisy estimate of the true signal subspace, we need to solve $\mathbf{S}_1\mathbf{h}_1 = \widetilde{\mathbf{U}}_s\mathbf{f}_1$ in the least square sense. Define, $\mathbf{D}_s \triangleq [\widetilde{\mathbf{U}}_s\mathbf{S}_1]$ and $\mathbf{x} \triangleq [\mathbf{f}_1^T \; -\mathbf{h}_1^T]^T$, then $\mathbf{h}_1$ is contained in the solution $\mathbf{x}$ to the following optimization problem,

$$\min_{\mathbf{x}\in C^{K+L}} \|\mathbf{D}_s\mathbf{x}\|^2 = \mathbf{x}^H\mathbf{D}_s^H\mathbf{D}_s\mathbf{x}, \text{ subject to } \|\mathbf{x}\|^2 = 1. \tag{3.43}$$

It is well known that the solution to (3.43) is given by the minimum eigen vector of the matrix $\mathbf{D}_s{}^H\mathbf{D}_s$. Using the penalty function method [19], the constrained optimization problem can be transformed into an unconstrained optimization problem. Based on the above discussion, an adaptive algorithm for joint channel estimation and multiuser detection is readily obtained as follows. At time n, suppose that the signal subspace obtained by the subspace-tracking algorithm, is $\widetilde{\mathbf{U}}_s(n)$. We form the matrix $\mathbf{D}_s(n) = [\widetilde{\mathbf{U}}_s(n) \;\; \mathbf{S}_1]$ and compute the matrix $\mathbf{B}(n) = \mathbf{D}_s(n)^H\,\mathbf{D}(n)$. We then apply one step of update on the estimated minimum eigen vector $\mathbf{x}(n)$ of $\mathbf{B}(n)$, according to the method of steepest descent,

$$\mathbf{x}(n) = \mathbf{x}(n-1) - \mu[\mathbf{B}(n)\mathbf{x}(n-1) + c(\|\mathbf{x}(n-1)\|^2 - 1)\mathbf{x}(n-1)] \tag{3.44}$$

where c is a positive constant. The estimated channel gain vector $\mathbf{h}_1(n)$ is a sub-vector of $\mathbf{x}(n)$. Upon normalization, the effective signature waveform $\widetilde{\mathbf{s}}_1(n)$ can be found.

3.4 INVERSE FILTERING CRITERIA FOR CDMA SYSTEMS

In this section we discuss linear blind CDMA receivers, which use inverse filtering criteria [20]. The approach is based on minimizing the receiver's output energy subject to appropriate constraints. This method is used in the multiuser case in [13] for synchronous and asynchronous users. The major advantage of this method is that no knowledge of the interfering users' codes is required. The algorithm only needs the code and timing of the desired user. Its major disadvantage, on the other hand, is that it cannot handle multipath effects. Constrained inverse filtering criteria is briefly explained now.

The mean output energy (MOE) is used as a cost function,

$$J_{MOE}(\mathbf{m}) = E\{\hat{\omega}_1^2(n)\} \tag{3.45}$$

where $\hat{\omega}_1(n)$ is the soft estimate of the nth data of the desired user (first user). If we define the vectors, $\mathbf{m} = [\mathrm{m}(1),..........,\mathrm{m}(\mathrm{q})]^{\mathrm{T}}$ and

$$\mathbf{r} = [\mathrm{r}(\mathrm{nN}+\mathrm{N}),\mathrm{r}(\mathrm{nN}+\mathrm{N}-1),.......,\mathrm{r}(\mathrm{nN}+\mathrm{N}-\mathrm{q}+1)]^{\mathrm{T}}$$

where, q is the filter order. Then,

$$\hat{\omega}_1(n) = \mathbf{m}^T\mathbf{r}(n) \tag{3.46}$$

$$\text{and} \quad J_{MOE} = \mathbf{m}^{\mathrm{T}}\mathbf{R}\mathbf{m} \tag{3.47}$$

where $\mathbf{R} = E\{\mathbf{r}(n)\mathbf{r}^T(n)\}$. It is clear from (3.47) that the cost function is minimised for $\mathbf{m}$=0. In order to avoid the trivial solution, $\mathbf{m}$ can be constrained to be $\mathbf{m}=\mathbf{s}_1+\mathbf{x}_1$, where $\mathbf{x}_1$ is orthogonal to the code vector $\mathbf{s}_1$ of the user 1. So, $\mathbf{m}^{\mathrm{T}}\mathbf{s}_1 = (\mathbf{s}_1^{\mathrm{T}} + \mathbf{x}_1^{\mathrm{T}})\,\mathbf{s}_1 = \|\mathbf{s}_1\|^2$

In practical systems, however, multipath effects and inaccuracies in the acquisition of the user's timing invalidate the ideal channel assumption. In a multipath scenario the above constraint is not meaningful and will not provide the desired results. In order to derive an appropriate constraint for the multipath case, let us denote by $a_1(n)$ the convolution of all the impulse response of the desired user,

$$a_1(n) = \sum_{l=1}^{L} h_1(l) c_1(n-l+1) \tag{3.48}$$

$$c_1(n) \triangleq \sum_{j=1}^{N} s_1(j) m(n-j+1) \tag{3.49}$$

Then, the overall impulse response for user 1 is $a_1(nN)$. Equation (3.48) and (3.49) can be written in matrix form for $a_1(nN), n = 1,2,3.......,M$ as,

$$\begin{bmatrix} c_1(N) & \cdots & c_1(N-L) \\ c_1(2N) & \cdots & c_1(2N-L) \\ \vdots & & \vdots \\ c_1(LN) & \cdots & c_1(MN-L) \end{bmatrix} \begin{bmatrix} h_1(1) \\ h_1(2) \\ \vdots \\ h_1(L) \end{bmatrix} = \begin{bmatrix} a_1(N) \\ a_1(2N) \\ \vdots \\ a_1(MN) \end{bmatrix} \tag{3.50}$$

or equivalently,

$$\mathbf{C}_1 \mathbf{h}_1 = \mathbf{a}_1 \tag{3.51}$$

with obvious notation. If $\mathbf{m}$ is such that user 1 is decorrelated, then we must have,

$$a_1(nN) = \alpha\delta(n-n_1), \quad i.e., \mathbf{a}_1 = \mathbf{C}_1 \mathbf{h}_1 = \alpha \mathbf{e}_{n_1} \tag{3.52}$$

where $\mathbf{e}_{n_1} = [0,\cdots,1,\cdots,0]^T$, has a one at the n_1 position with n_1 an arbitrary delay. In order to guarantee the recovery of the desired user, we need a constraint that will yield (3.52), regardless of the value of $\mathbf{h}_1$. To this end, a constraint matrix can be proposed as under

$$\mathbf{C}_l = \beta \begin{bmatrix} 0\,0 \cdots 0 \\ \vdots\ \vdots \quad \vdots \\ 1\,0 \cdots 0 \\ \vdots\ \vdots \quad \vdots \\ 0\,0 \cdots 0 \end{bmatrix} \tag{3.53}$$

for some scalar $\beta \neq 0$. If $\mathbf{C}_l$ is given as above, then clearly, (3.52) is satisfied for any $h_l(l)$, provided that $h_l(1) \neq 0$ and $\alpha = h_l(1)\beta$.

3.5 MINIMUM VARIANCE RECEIVERS

In the absence of multipath (L=1), $\tilde{\mathbf{s}}_l = \mathbf{s}_l h_l$, where h_l is the attenuation factor and $\mathbf{s}_l = [s_l(1), \ldots\ldots, s_l(N)]^T$. In that case, the constraint $\mathbf{m}^H \mathbf{s}_l = 1$ guarantees no signal cancellation and minimisation of (3.47) results in solutions with performance identical to that of the MMSE receiver.

Unfortunately, constrained optimisation methods are known to be very sensitive to signature mismatch due to signal cancellation effects [21]. Hence special care needs to be taken when multipath is present. If the multipath signature $\tilde{\mathbf{s}}_l$ were known, the constraint $\mathbf{m}^H \tilde{\mathbf{s}}_l = 1$, could be used resulting in the solution [22],

$$\mathbf{m}_{mv} = (\tilde{\mathbf{s}}_l^H \mathbf{R}^{-1} \tilde{\mathbf{s}}_l)^{-1} \mathbf{R}^{-1} \tilde{\mathbf{s}}_l \tag{3.54}$$

and the minimum output energy (MOE) at the optimal point becomes,

$$\mathrm{MOE}(\tilde{\mathbf{s}}_l) = \mathbf{m}_{mv}^H \mathbf{R} \mathbf{m}_{mv} = \frac{1}{\tilde{\mathbf{s}}_l^H \mathbf{R}^{-1} \tilde{\mathbf{s}}_l} \tag{3.55}$$

where $\tilde{s}_1 = \mathbf{S}_1\mathbf{h}_1$, $\mathbf{S}_1 = \begin{bmatrix} s_1(1) & & 0 \\ \vdots & \cdots & \vdots \\ s_1(N) & \cdots & s_1(1) \\ \vdots & & \vdots \\ 0 & & s_1(N) \end{bmatrix}$ and $\mathbf{h}_1 = \begin{bmatrix} h_1(1) \\ \vdots \\ h_1(L) \end{bmatrix}$

Hence, $\tilde{s}_1$ depends on the unknown multipath parameters $\mathbf{h}_1$ and is generally not known. One approach for handling mutipath case relies on extending the number of constraints. In [20], the receiver vector was constrained to $\mathbf{S}_1^H\mathbf{m} = [1,0,\cdots,0]^T$. In this way the response of the signal of interest was constrained to,

$$\mathbf{m}^H\tilde{s}_1 = \mathbf{m}^H\mathbf{S}_1\mathbf{h}_1 = [1,0,\cdots,0]\mathbf{h}_1 = h_1(0) = \text{constant} \tag{3.56}$$

Since $h_1(0) \neq 0$, this method avoids the signal cancellation problem by forcing the response of the delayed copies of the signal interest to zero. In doing so, however, the method does not exploit all the energy of the received signal and results in suboptimal performance.

It can be seen from above discussion that, there is a need for treating the multipath problem more rationally, in order to exploit the energy of all paths. To this end we modify the constraint of (3.56) by forcing $\mathbf{m}$ to satisfy,

$$\mathbf{S}_1^H\mathbf{m} = \mathbf{h} \tag{3.57}$$

where $\mathbf{h}$ is a general parameter vector, which can be arbitrarily chosen.

SINR analysis

In the sequel, we derive analytical expressions to compare minimum variance methods with each other and with the MMSE solution. We use the output signal to interference and noise ratio (SINR) as the figure of merit. From [22], SINR_{mse} can be written as,

$$SINR_{mse} = \frac{1}{\frac{1}{A_1^2 \tilde{\mathbf{s}}_1^H \mathbf{R}^{-1} \tilde{\mathbf{s}}_1} - 1} \tag{3.58}$$

On the other hand, if we consider the minimum variance solution subject to the constraint (3.57), we obtain the optimal receiver using the method of Lagrange multipliers as,

$$\mathbf{m}_{mv} = \mathbf{R}^{-1}\mathbf{S}_1\left(\mathbf{S}_1^H \mathbf{R}^{-1}\mathbf{S}_1\right)^{-1}\mathbf{h} \tag{3.59}$$

Moreover, the receiver's output energy can be shown to be,

$$MOE(\mathbf{h}) = \mathbf{h}^H\left(\mathbf{S}_1^H \mathbf{R}^{-1}\mathbf{S}_1\right)^{-1}\mathbf{h} \tag{3.60}$$

Substituting (3.59) in the SINR formula (3.58) and using $\tilde{\mathbf{s}}_1 = \mathbf{S}_1\mathbf{h}_1$, we obtain,

$$SINR\ (\mathbf{h}) = \frac{1}{\frac{\mathbf{h}^H\left(\mathbf{S}_1^H \mathbf{R}^{-1}\mathbf{S}_1\right)^{-1}\mathbf{h}}{A_1^2\left\|\mathbf{h}^H\mathbf{h}_1\right\|^2} - 1} \tag{3.61}$$

It is well known that MMSE receiver maximises the SINR; hence in general

$$\mathrm{SINR}(\mathbf{h}) \leq \mathrm{SINR}_{mse} \tag{3.62}$$

This discussion reveals the importance of the choice of $\mathbf{h}$ in system performance. It is clear from (3.59) that if $\mathbf{h}$ is chosen as,

$$\mathbf{h} = A_1^2\left(\mathbf{S}_1^H \mathbf{R}^{-1}\mathbf{S}_1\right)^{-1}\mathbf{h}_1 \tag{3.63}$$

then, equality is satisfied in (3.62), because $\mathbf{m}_{mv}$ is now identical to the MMSE equalizer. Although (3.63) provides an optimal constraint, it requires the knowledge of the channel parameters $\mathbf{h}_1$, which may not be available in a blind setup.

An approach to optimise $\mathbf{h}$ when no channel parameters are *a priori* known might be to maximize the output signal power after the interference has been suppressed. This max/min problem is equivalent to

$$\max_{h} \frac{MOE(\mathbf{h})}{\|\mathbf{h}\|^2} = \max_{\mathbf{h}} \frac{\mathbf{h}^H \left(\mathbf{S}_1^H \mathbf{R}^{-1} \mathbf{S}_1\right)^{-1} \mathbf{h}}{\mathbf{h}^H \mathbf{h}} \tag{3.64}$$

The cost function in (3.64) is a Raleigh quotient, and hence, the solution to the optimization problem is the eigen vector of $\left(\mathbf{S}_1^H \mathbf{R}_y^{-1} \mathbf{S}_1\right)^{-1}$ corresponding to the maximum eigen value (or equivalently, the minimum eigen vector of $\left(\mathbf{S}_1^H \mathbf{R}^{-1} \mathbf{S}_1\right)$). It would be interesting, therefore, in order to assess the performance of this approach, to evaluate (3.61) when $\mathbf{h}$ is the minimum eigen vector of $\left(\mathbf{S}_1^H \mathbf{R}^{-1} \mathbf{S}_1\right)$. Let $\mu_1 \le \cdots \le \mu_L$ *and* $v_1, \cdots, v_L$ denote the eigenvalues and corresponding eigen vectors of $\left(\mathbf{S}_1^H \mathbf{R}^{-1} \mathbf{S}_1\right)^{-1}$, respectively, and let $\mathbf{h} = \mathbf{v}_1$, then (3.61) becomes

$$SINR(\mathbf{v}_1) = \frac{1}{\frac{1}{\mu_1 A_1^2 \|\mathbf{v}_1^H \mathbf{h}_1\|^2} - 1} \tag{3.65}$$

Notice that the SINR in (3.65) is a monotone increasing function of $T_1 = \mu_1 \|\mathbf{v}_1^H \mathbf{h}_1\|^2$ where as $SINR_{mse}$ is a monotone increasing function of,

$$T_{mse} = \tilde{\mathbf{s}}_1^H \mathbf{R}^{-1} \tilde{\mathbf{s}}_1 = \mathbf{h}_1^H \mathbf{S}_1^H \mathbf{R}^{-1} \mathbf{S}_1 \mathbf{h}_1 = \sum_{l=1}^{L} \mu_l \|\mathbf{v}_l^H \mathbf{h}_1\|^2 \tag{3.66}$$

Equation (3.66) demonstrates the suboptimal nature of the proposed method since,

$$T_{mse} = T_1 + \sum_{l=1}^{L} \mu_l \|\mathbf{v}_l^H \mathbf{h}_1\|^2 \ge T_1 \tag{3.67}$$

3.6 TIMING-FREE BLIND MULTIUSER DETECTION

A timing-free blind multiuesr detection technique is proposed for differentially encoded DS/CDMA networks in [23]. Unlike previously derived blind multiuser detectors, the proposed algorithm does not rely on any information beyond the spreading code of the desired user, namely neither the complex amplitude nor the symbol timing of the signal of interest is assumed to be known to the receiver. The proposed receiver is immune to co-channel interferers with arbitrarily large powers and achieves performance quite close to that of the ideal MMSE receiver which requires the knowledge of the spreading codes, timing offsets, and received energies for the signals of all active users.

The detection algorithm proposed here, does not rely on any channel state information, nor does it rely on pilot symbols, which necessitates the adoption of differential encoding and decoding. The information in the *n*th signalling interval is contained in the symbols $b_l(n)$ and $b_l(n-1)$, and the decision rule of a corresponding linear multiuser detector is,

$$\hat{b}_1(n) = \mathrm{sgn}\left[\mathrm{Re}\left\{\left(\mathbf{m}^H \mathbf{r}(n)\right)\left(\mathbf{m}^H \mathbf{r}(n-1)\right)\right\}\right] \tag{3.68}$$

where $\mathrm{sign}\,(\cdot)$ and $\mathrm{Re}(\cdot)$ denote the signum function and real part, respectively, and $\hat{b}_1(n)$ is the incremental phase between $b_l(n)$ and $b_l(n-1)$. In the equation, $\mathbf{m}$ is a detector vector to be suitably designed.

The receiver structure considered is depicted in Fig. 3.7. It is a two-stage structure, where the fist stage is aimed at multiaccess interference suppression, while the second stage carries out optimization with respect to noise and unknown parameters. The vector $\mathbf{m}$ in (3.68) is obtained as the product $\mathbf{De}$, where $\mathbf{D}$ and $\mathbf{e}$ are to be suitably chosen.

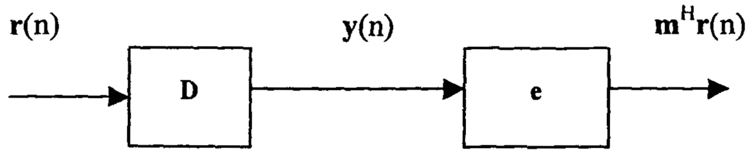

Fig. 3.7 Block schematic of the linear receiver

Synthesis of the interference cancellation stage

Here we can write $\mathbf{y}(n)=\mathbf{D}^H\,\mathbf{r}(n)$ where $\mathbf{D}$ is a 2NP x (NP+1) rectangular matrix with P, the over sampling factor and N, the processing gain. Using the method of Lagrange multipliers,

$$\mathbf{D} = \mathbf{R}^{-1}\mathbf{S}_1[(\mathbf{S}_1^H\mathbf{R}^{-1}\mathbf{S}_1)] \tag{3.69}$$

with $\mathbf{R}=E[\mathbf{r}(n)\mathbf{r}^H(n)]$, the covariance matrix of the observables, and $\mathbf{S}_k = \begin{bmatrix}\mathbf{s}_k^{(0)} & \mathbf{s}_k^{(1)} & \cdots & \mathbf{s}_k^{(NP)}\end{bmatrix}$

$$\text{with}\,\mathbf{s}_k^{(\ell)} = \left[\underbrace{0,\cdots,0}_{\ell},\underbrace{s_k(1),\cdots,s_k(1)}_{P},\cdots\cdots,\underbrace{s_k(N),\cdots,s_k(N)}_{P},\underbrace{0,\cdots,0}_{NP-\ell}\right]^T$$

Synthesis of second stage of the receiver

Towards designing second stage of the receiver, we make the assumption that the MAI has essentially been removed by, the blocking matrix $\mathbf{D}$, so that the transformed observables can be written approximately as

$$\mathbf{y}(n) = b_1(n)\mathbf{D}^H\mathbf{S}_1\mathbf{h}_1 + \mathbf{D}^H\mathbf{n}(n) \tag{3.70}$$

Even though this is only an approximation, the transformation $\mathbf{D}$ is able to reject a considerable amount of the MAI energy, and it zero-forces those signals with large amplitudes. Given the transformed observables in (3.70), we choose the vector **e** to maximise the signal-to-noise ratio. Were $\mathbf{h}_1$ a known vector, the optimum processing would simply consist of a whitening transformation followed by a filter matched to the whitened useful signal. The whitened observables are given as,

$$\mathbf{y}_w(n) = b_1(n)\mathbf{L}^{-1}\mathbf{D}^H\mathbf{S}_1\mathbf{h}_1 + \mathbf{L}^{-1}\mathbf{D}^H\mathbf{n}(n) \tag{3.71}$$

where, **L** is contained in the Choleskey factorisation of $\mathbf{D}^H\mathbf{D} = \mathbf{L}\mathbf{L}^H$. Now, since prior knowledge as to the vector $\mathbf{h}_1$ is assumed, a further step is necessary in order to obtain an estimate of the unknown matched filter. To this end, we observe that the covariance matrix of the observables is given by

$$\mathbf{Y} = E[\mathbf{y}_w(n)\mathbf{y}_w^H(n)] \tag{3.72}$$

The NP eigenvalues of this matrix are coincident, while the eigenvector, **v** corresponding to the largest eigenvalue is parallel to $\mathbf{L}^{-1}\mathbf{D}^H\mathbf{S}_1\mathbf{h}_1$. The vector **e** appearing in Fig. 3.7 is thus given by the product of the matrix $(\mathbf{L}^{-1})^H$ times such an eigen vector. Finally the vector **m**, needed to implement the decision rule (3.68) is expressed as $\mathbf{m} = \mathbf{D}(\mathbf{L}^{-1})^H\mathbf{v}$.

3.7 CONCLUSION

In this chapter we have discussed different multiuser detectors available in literature. The optimum detector is found to be too complex for practical implementations. Sub-optimal detectors like decorrelators and MMSE detectors are the most common linear detectors. The adaptive versions of these detectors are also presented. A blind, adaptive MMSE detection criterion using LMS algorithm was then introduced which forms the basis of our work presented in the coming chapters. The formation of linear detectors using subspace method also was discussed. A blind method for channel estimation using subspace method was then presented. The minimum variance multiuser detectors and the inverse filtering criterion as applied to CDMA systems were presented next. A timing multiuser detector, which does not use knowledge regarding, the timing of the desired user also was presented towards the end. In the next chapter we discuss different preliminary works undertaken.

Chapter 4

PREPARATARY WORKS

4.1 INTRODUCTION

In this chapter various preliminary works undertaken and their performance analysis is discussed. The performance of conventional matched filter, decorrelating detector (decorrelator) and MMSE detector is validated first. In this case detectors are formed with the knowledge of the signature codes of all users, signal amplitude etc. Next a data-aided adaptive MMSE detector is formed and the performance is validated. Blind versions of detectors are then developed and tested. Minimum variance and subspace methods are then simulated. The subspace-tracking algorithm is also attempted. Channel estimation using subspace method is also tried.

4.2 CONVENTIONAL MATCHED FILTER

Single-user matched filter or conventional matched filter (CMF) is the simplest detector for demodulating CDMA signals. CMF is an optimum receiver in single-user channel (only one user using the channel). But in a multiuser channel (More than one user using the channel), CMF ceases to be an optimum receiver when the signature codes of the users are non-orthogonal. This detector neglects the presence of other users in the channel and assumes that aggregate noise plus interference is white and gaussian. Fig. 4.1 is a plot of the bit error rate for the first user as a function of SNR, for two amplitudes of the interferer. We can observe the degradation of the BER, when the interfering user's amplitude changes from zero to

$2A_1$.The performance degradation due the presence of other users is termed as near-far problem in multiuser communications.

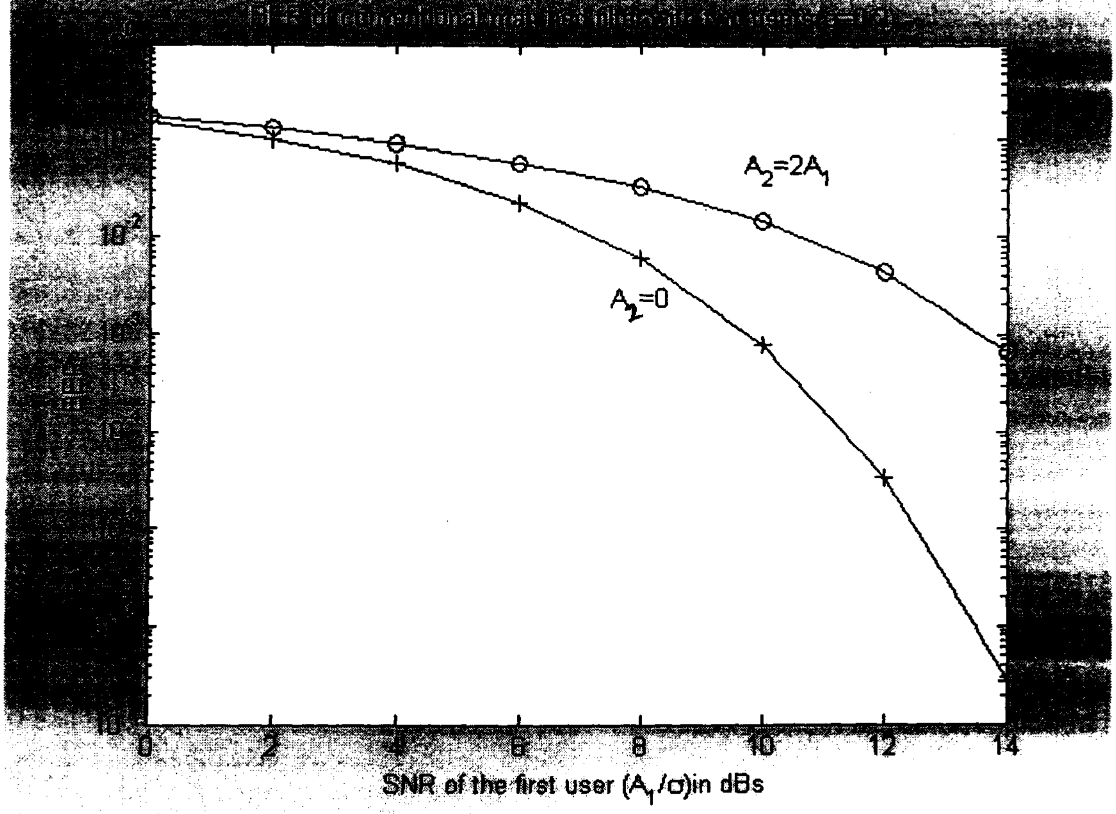

Fig 4.1 BER of the Conventional matched filter

4.3 DECRRELATING DETECTOR

Bit error performance of the decorrelator and CMF is compared in Fig. 4.2. It can be seen that bit error performance of the decorrelator is independent of the interferer's amplitude, while the performance of the CMF is dependent on the amplitude of the interferer. In this respect decorrelator is near-far resistant. It can also be verified that at low SNRs there is no special advantage with the decorrelator and at very low SNRs the performance of the decorrelator is inferior to the CMF.

Moreover the decorrelator is not that attractive as the amplitude of the interferer comes down.

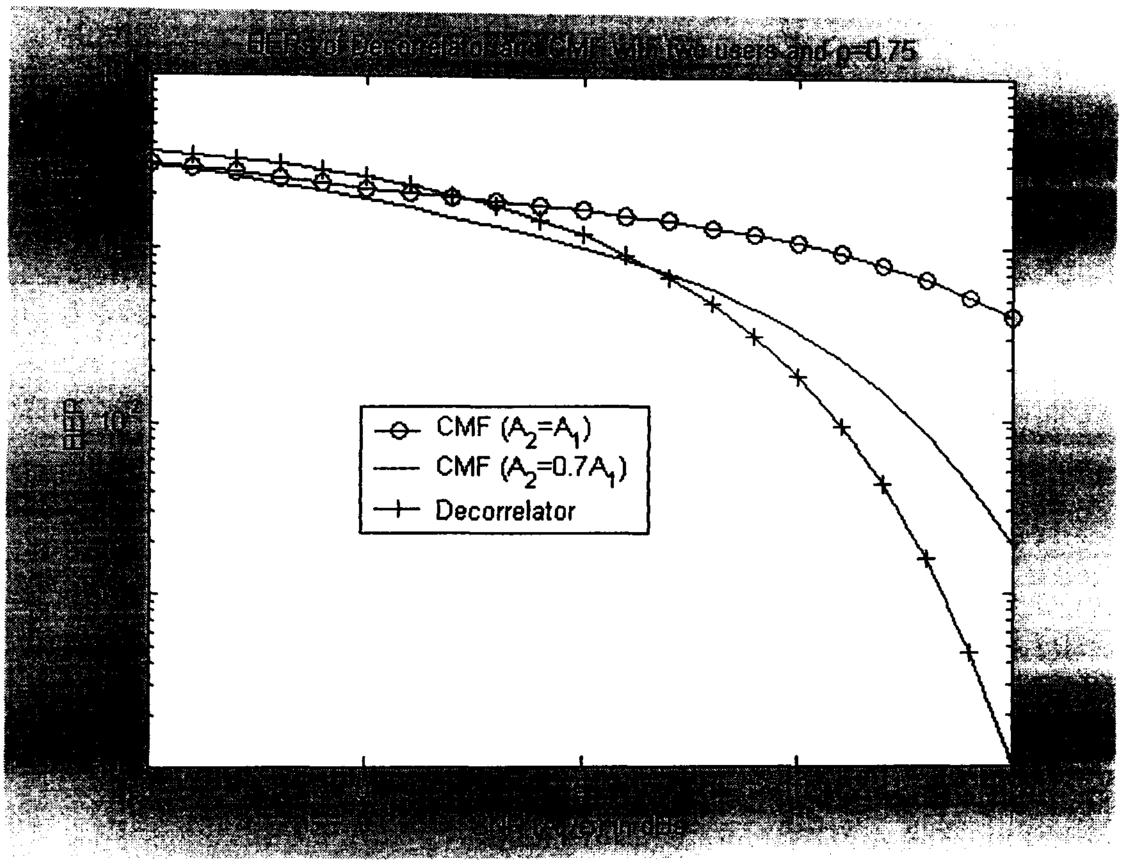

Fig. 4.2 BER comparison of the Decorrelator and CMF

4.4 MMSE DETECTOR

The conventional matched filter is optimized to combat the background white noise exclusively, whereas the decorrelating detector eliminates the multiuser interference disregarding background noise. In contrast, the MMSE linear detector can be seen as a compromise solution that takes into account the relative importance of each interfering user and background noise. In fact both conventional receiver and decorrelating receiver are limiting cases of MMSE linear detector. As MMSE detector converges to the decorrelating detector when $\sigma \rightarrow 0$, its asymptotic multiuser efficiency and near-far resistance are identical to that of the decorrelator. The chief advantage of MMSE detector is the ease with which it can be implemented adaptively.

The Fig. 4.3 compares the BERs of the conventional matched filter, decorrelator and MMSE detector for two users with cross-correlation equal to 0.8. The SNR of the desired user is equal to 10 dB. The probability of error is shown against the near-far ratio A_2/A_1. Note that for sufficiently low interferer power, the probability of error of MMSE detector is better than that of the decorrelator. For relatively high-power interferers, the MMSE detector is quite similar to the decorrelator and much better than the conventional matched filter.

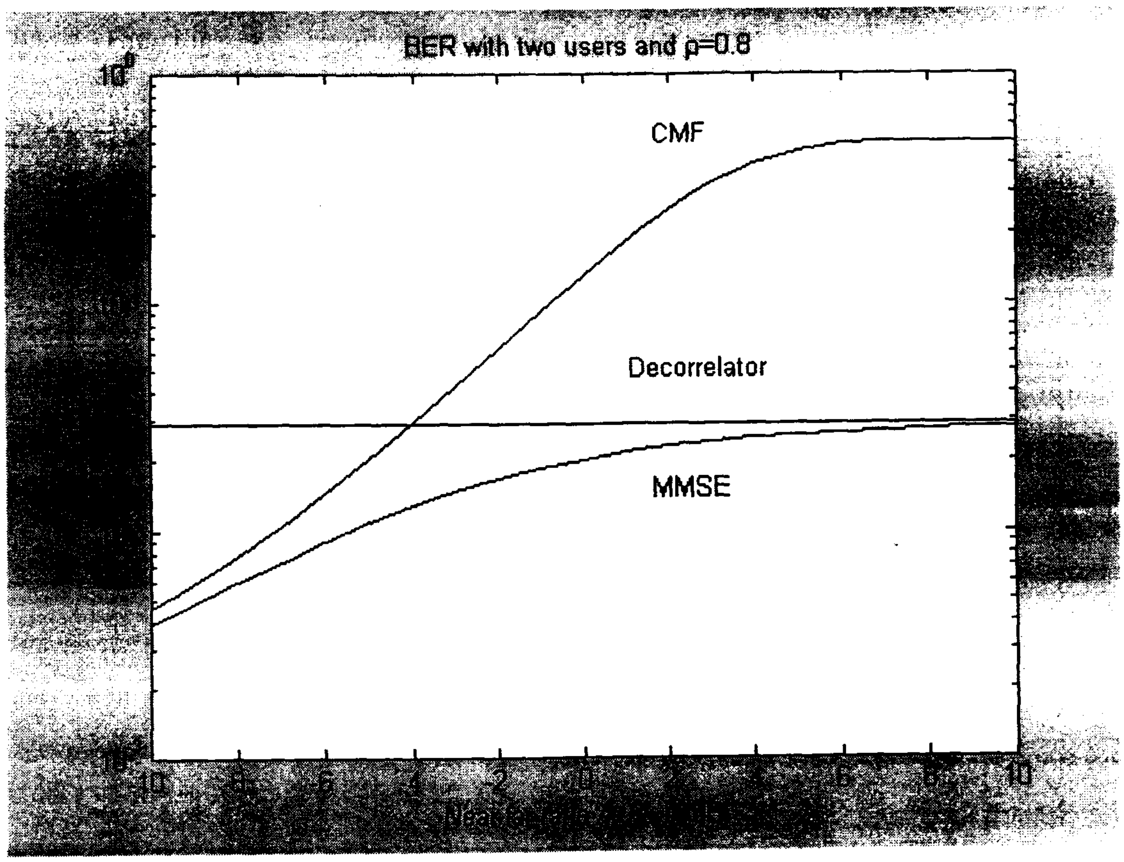

Fig. 4.3 BER comparison of CMF, Decorrelator and MMSE receiver at SNR=10 dB

4.5 ADAPTIVE IMPLEMENTATION

From chapter 3, it was clear that the formation of a decorrelator requires the cross correlation matrix of the signature codes and its inversion. MMSE detector additionally requires signal and noise amplitudes for its implementation. The complexity arising out of matrix inversion can be totally avoided by using adaptive implementations. It is particularly important to eliminate the need to compute the linear detector impulse response in asynchronous channels where cross correlations are time varying and in channels with time varying characteristics. It is desirable to have detector that do not require the knowledge of signal and noise amplitudes and signature codes of the users. The adaptive implementation of the receiver meets these requirements.

The training sequence-based (data-aided) adaptive MMSE detector learns the desired filter impulse response, from the received data provided the received sequence is previously known to the receiver. The bit error performance of a training based MMSE detector [9, Sec. 6.4] is contrasted with that of the non-adaptive MMSE detector in a three-user system in Fig. 4.4. Here we have used the technique of stochastic gradient descent, using LMS algorithm. It can be seen that performance-wise there is no much difference between adaptive and non-adaptive methods.

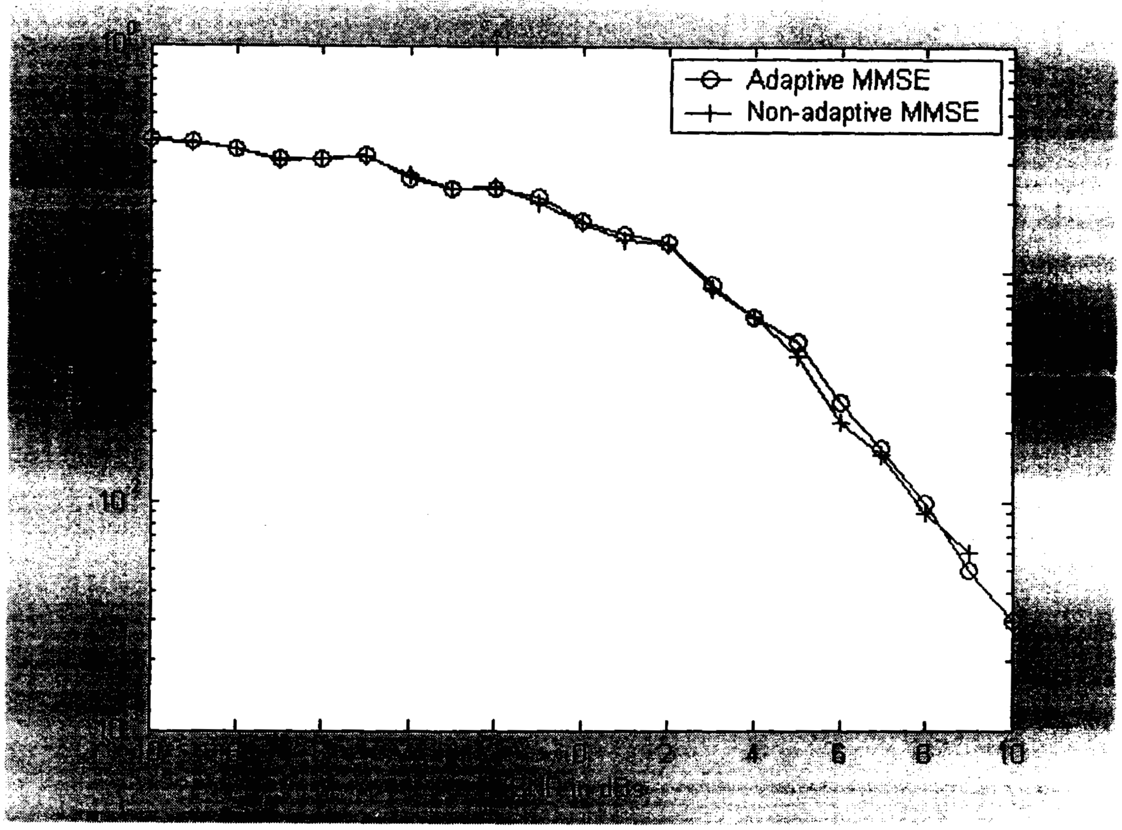

Fig. 4.4 BER comparison of adaptive and non-adaptive MMSE receiver

4.6 BLIND METHODS

4.6.1 Direct matrix inversion

A blind detector can be implemented either in batch mode or in adaptive mode. If the autocorrelation matrix of the received signal, $\mathbf{R} = \mathrm{E}\{\mathbf{r}\mathbf{r}^H\}$, is given then the MMSE detector $\mathbf{m}_1$ is determined as

$$\mathbf{m}_1 = |\mathbf{A}_1|^2 \mathbf{R}^{-1}\mathbf{s}_1 \tag{4.1}$$

Note that, $\mathbf{R}$ can be estimated from the received signals by the corresponding sample autocorrelation. The above equation, leads straight forwardly, to the blind implementation of the linear MMSE detector, resulting detector is called, direct matrix inversion (DMI) blind detector [24]. Here we do not assume knowledge of the amplitude of the desired user, so differential detection is employed as shown,

$$
\begin{aligned}
&\hat{\mathbf{R}} = 1/M\sum_{n=1}^{M}\mathbf{r}(n)\mathbf{r}(n)^{H}, \text{ where M is the symbol length} \\
&\hat{\mathbf{m}}_1 = \hat{\mathbf{R}}^{-1}\mathbf{s}_1 \\
&z_1[n] = \hat{\mathbf{m}}_1^{H}\mathbf{r}[n] \\
&\hat{\beta}_1[n] = \text{sign}\{\text{Re}(z_1[n]z_1[n-1]^{*}\}
\end{aligned}
\qquad (4.2)
$$

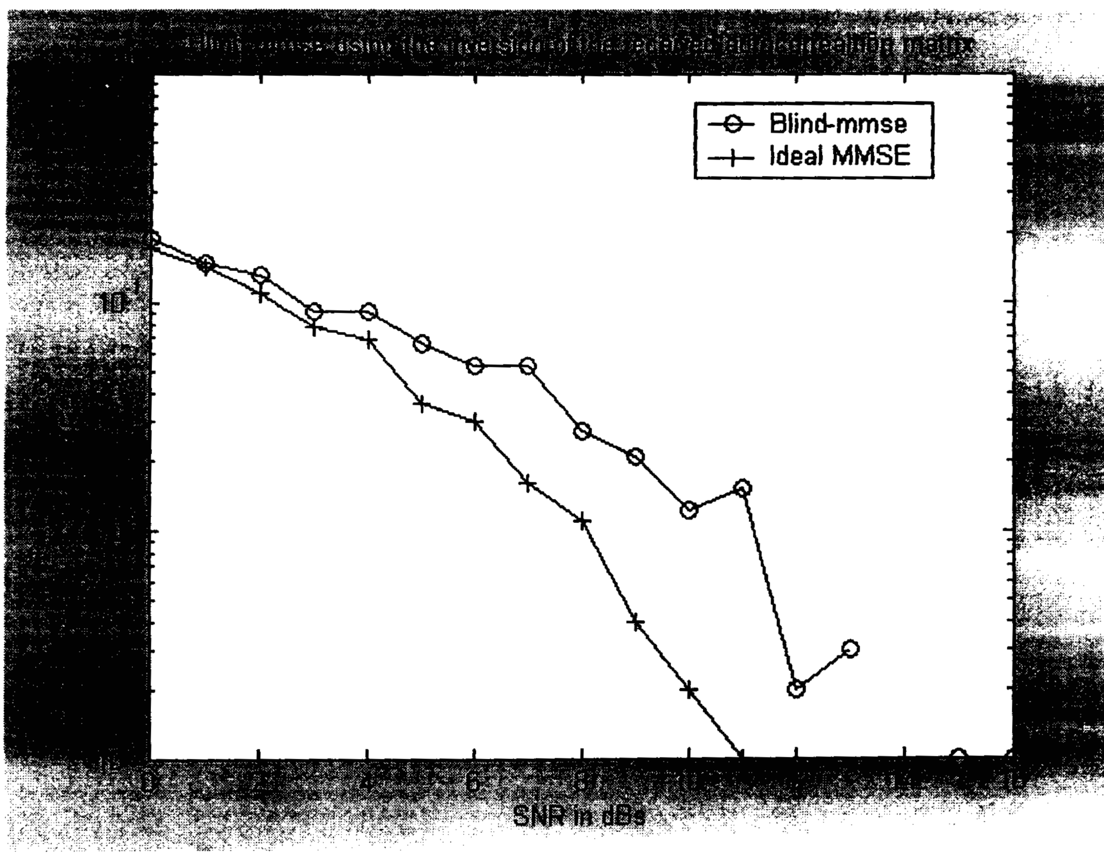

Fig. 4. 5 Blind MMSE detector using DMI

The above method is a batch process method, which computes the detector only once, based on a block of received signals $\{\mathbf{r}[n]\}_{i=1}^{M}$. The performance comparison is shown in Fig. 4.5

4.6.2 Blind adaptive implementations

MOE-LMS

In this section we discuss the performance of a blind, adaptive detector that converges to the MMSE detector without requiring training sequences. The knowledge required by the detector presented in this section is identical to the knowledge required by the conventional matched filter (CMF) receiver, namely the signature code and timing of the desired user. The approach we adopt here is same as the training based system, namely, stochastic gradient descent of a convex penalty function. In this case the penalty function is the output variance instead of mean squared error. This method is termed as minimum output energy (MOE) method.

In Fig. 4.6, we have demonstrated the close relationship between MOE and MMSE methods. It has been established that there is no theoretical difference between MOE and MMSE methods [9,13].

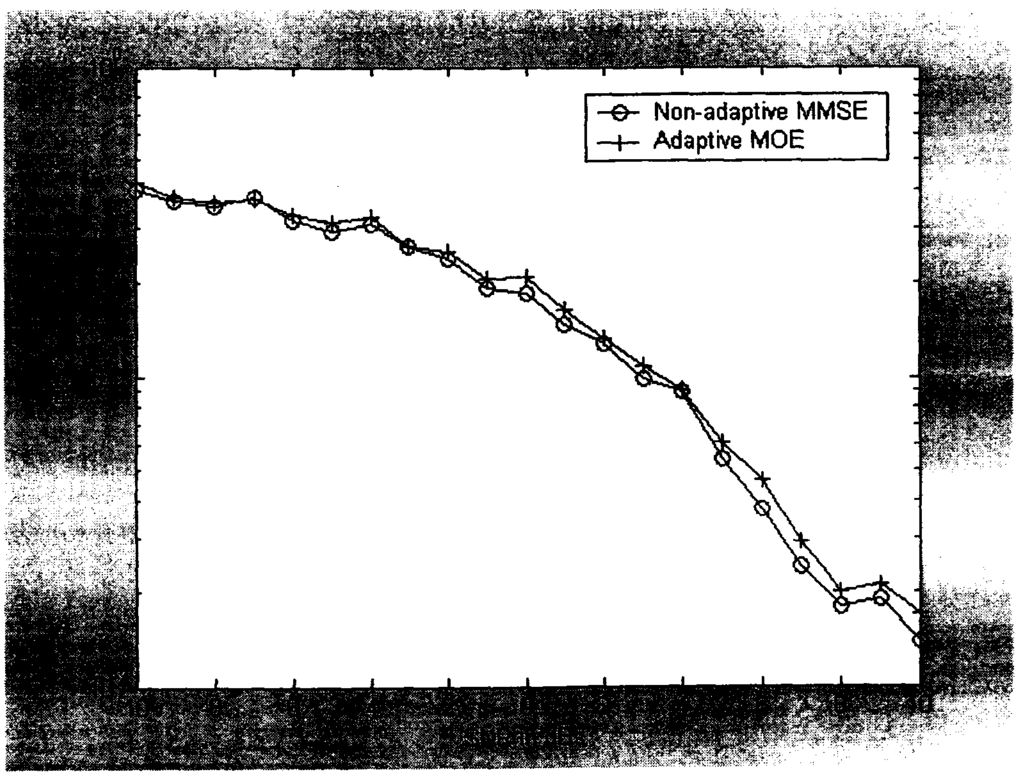

Fig. 4.6 Performance comparison of adaptive MOE-LMS and ideal MMSE

MOE-RLS

Here we are assessing convergence dynamics of an adaptive, blind MMSE detector formed, using MOE criterion and RLS algorithm. PN codes of length 31, are used as the signature codes. There are three interferers at 5, 10 and 20dBs in addition to the desired user. The powers of the interferers are given with respect to the desired user. The SNR after dispreading is 10dB. BER is calculated for 1000 simulations at the intervals of two iterations as shown in Fig. 4.7. The performance of an ideal MMSE detector operating under identical conditions is also given for comparison.

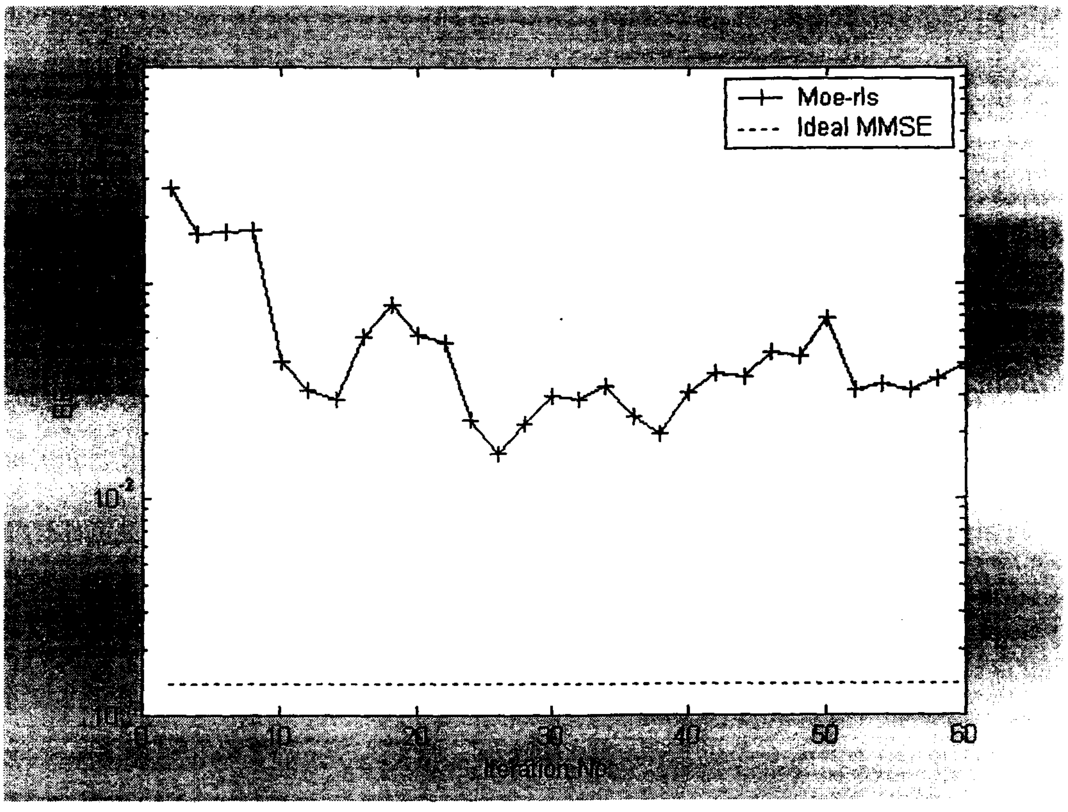

Fig. 4.7 Performance of MOE-RLS and ideal MMSE

4.7 MINIMUM VARIANCE RECEIVERS

Here we are assessing the performance of minimum variance receivers proposed by Tsatsanis [22]. In the simulations we have four interferers at various power levels from 4 to 10 dBs relative to the desired user. The desired user has two paths. The performance measure compared is, SINR of the receiver proposed by Tsatsanis and the ideal MMSE receiver. It can be seen from Fig. 4.8, that at low SNRs, the performance of the receiver by Tsatsanis is inferior to the ideal MMSE receiver. As the SNR improves the performance of this receiver approaches that of the ideal receiver. Equations (3.58) and (3.65) are used for calculating $SINR_{mse}$ and $SINR_{Ts}$, respectively.

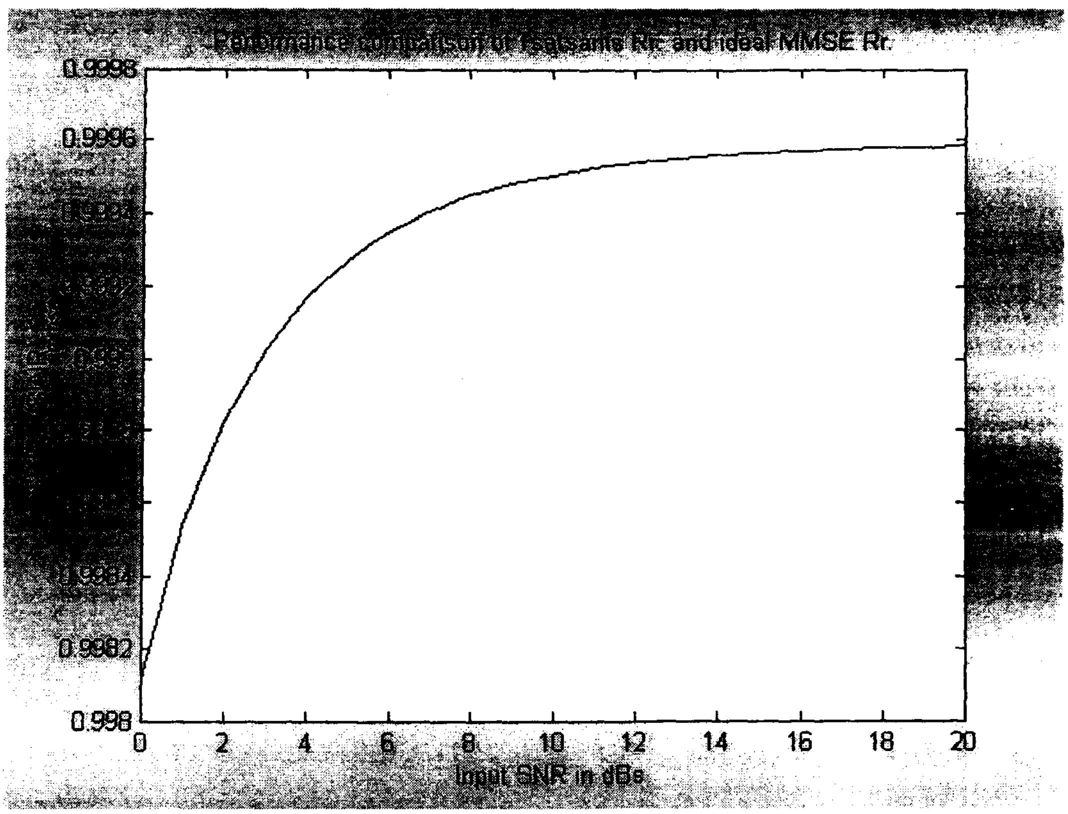

Fig. 4.8 Tsatsanis receiver and ideal MMSE receiver

4.8 SUBSPACE METHODS

4.8.1 Batch method

Based on signal subspace estimation, both the decorrelating detector and the linear MMSE detector can be obtained blindly, as explained in sec. 3.3.2. Fig. 4.9

compares the performance of such a blind MMSE detector and the ideal MMSE detector. The number of users is 6 and the subspace parameters are derived from a batch of 120 data samples. The received data is subjected to SVD to identify the subspace parameters. The amplitude of the interferers varies from 0 to 20dB. The signature code used is gold code of length 31. The performance of the subspace method is inferior to the ideal MMSE detector, because in the former subspace parameters are derived from the noisy, received signal.

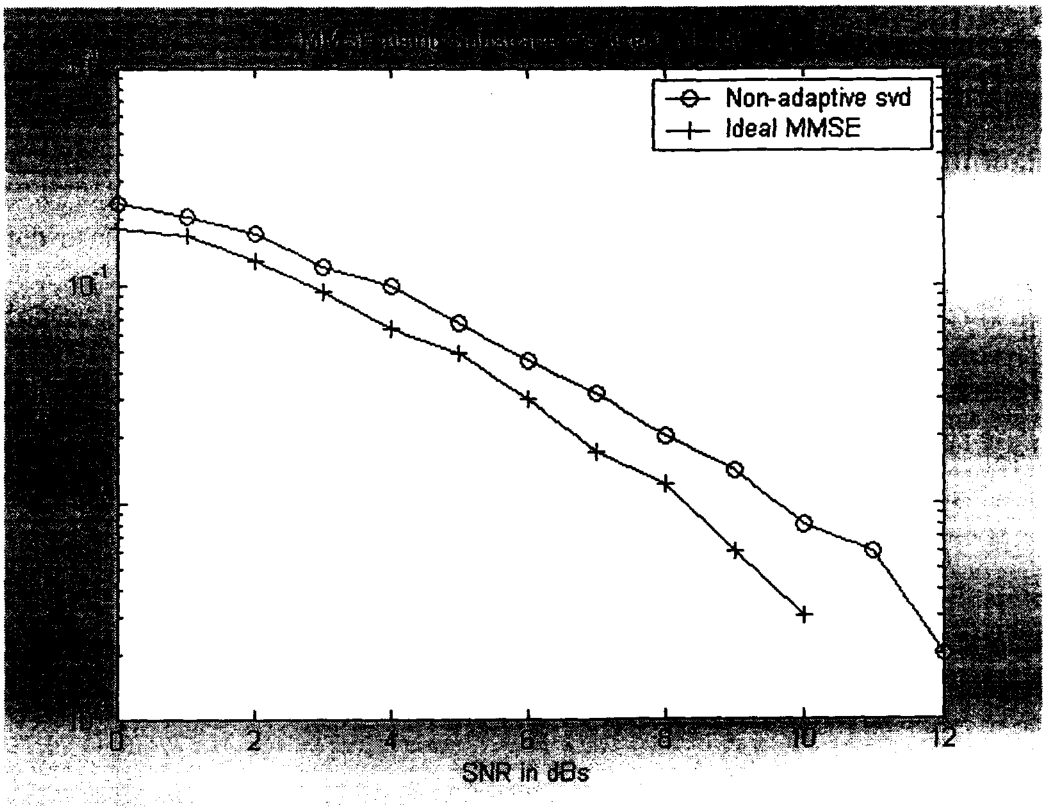

Fig. 4.9 MMSE receiver using subspace method and ideal MMSE.

4.8.2 Subspace-tracking

Modern subspace tracking algorithms are recursive in nature and update the subspace in a sample-by-sample fashion. Various subspace-tracking algorithms exist in literature. Here we adopt the recently proposed projection approximation subspace tracking by deflation (PASTd) algorithm, as explained in Sec. 3.3.3. The advantages of this algorithm include almost sure global convergence to the signal eigen vectors and eigen values and low computational complexity of O(NK), when compared to the RLS version of the MOE blind adaptive detector.

It assumes a synchronous CDMA system with processing gain 31 and six users. The desired user is the first user. The amplitudes of the five interferers vary from 0 to 20dB. The forgetting factor used is 0.997 and the input SNR is 10dB. The performance measure is BER Vs the number of iteration of the subspace-tracking algorithm and is shown as solid line in Fig. 4.10. The BER is averaged over 1000 simulations each with 10 iterations. It can be seen that BER is high initially and comes down after some 120x10 iterations. Even after this stage, fluctuation in BER is observed. For comparison, the performance of an ideal MMSE detector, working under identical conditions is also shown in dotted lines.

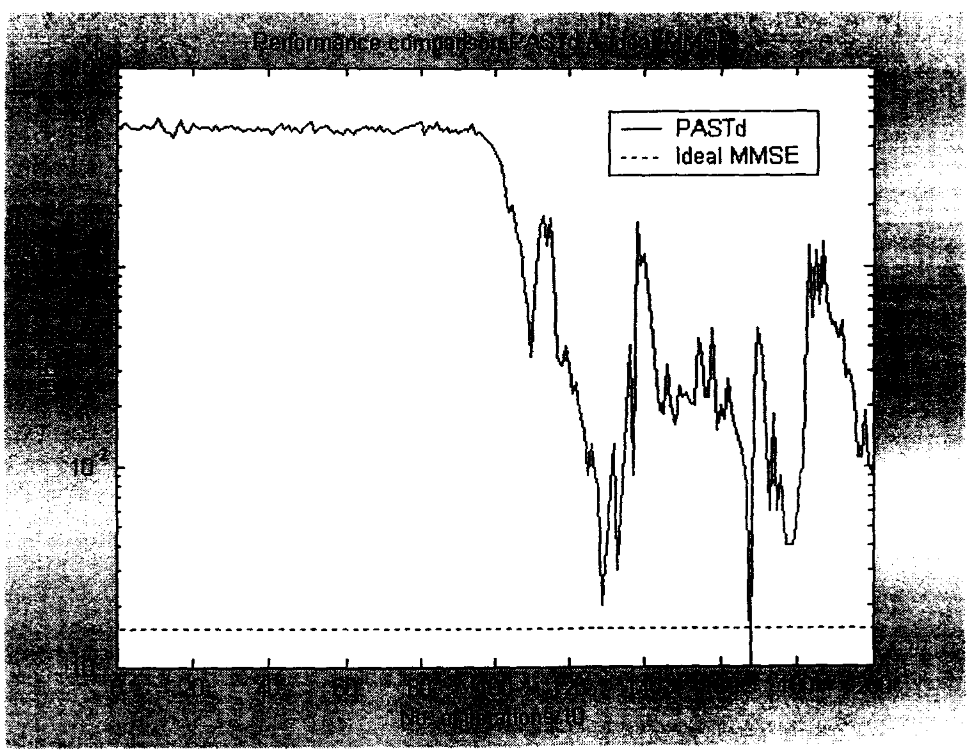

Fig. 4.10 Subspace tracking method and ideal MMSE

4.8.3 Channel estimation

When the signal is transmitted over a multipath channel, at the receiver end, the effective signature waveform is the multipath channel response to the original signature waveform. Subspace-based batch methods have been proposed for blind multipath channel estimation and blind, effective signature code estimation [16]. This is explained in sec. 3.3.1.

A blind channel estimation scheme was conducted for two users when each user has two paths. Here we are making use of the fact that signal subspace is orthogonal to the noise subspace. Once we estimate the channel response, the effective signature code can be estimated, which in turn can be used in subspace-based algorithms to identify the decorrelating or MMSE detector. An adaptive channel estimation scheme is proposed in [15], which can be coupled with subspace tracking algorithms to get a blind adaptive channel estimation and data detection scheme in a multipath scenario.

4.9 CONCLUSION

This chapter gives the implementation issues of the basic detectors like conventional matched filter, decorrelator and MMSE detectors. It can be seen from the figures that these basic detectors are behaving as expected. The data-aided MMSE and ideal MMSE are compared and no perceptible differences were observed. The performance of the DMI-MMSE detector was then verified to be inferior to the ideal MMSE receiver, probably because the autocorrelation matrix was derived from the received signal itself. An MOE detector using LMS and RLS algorithm was then tested. It can be seen that MOE-LMS detector outperforms the

MOE-RLS detector. Subspace method in batch mode and in tracking mode also was experimented. It was seen that, in addition to its increased computational complexity, subspace-tracking algorithm fails to deliver reliable results. In the next chapter we discuss the proposed detector.

Chapter 5: Proposed Work

BLIND ADAPTIVE MULTIUSER DETECTION WITH INTEGRATED CHANNEL ESTIMATION

5.1 INTRODUCTION

In the proposed work a blind, adaptive multiuser receiver for CDMA channels with integrated channel estimation is considered. The proposed receiver requires only the signature code of the user of interest (UOI) and does not require any training sequences, the channel parameters and signature codes of the interfering users. In a dynamic channel scenario, the tracking of the channel is done adaptively with reduced computational complexity. Though the channel parameters of the UOI are not explicitly calculated, the energies of multiple paths are advantageously combined as done in a conventional RAKE receiver. After removing the multiple access interference (MAI), the signal-to-noise ratio (SNR) of the system is improved using the max/min criterion. The performance of the receiver matches that of a non-adaptive, non-blind MMSE receiver and its performance in a mobile, fading environment is found to be encouraging. In a high SNR scenario, no updation of the receiver filter is needed when the channels of the interfering users change and only a few computations are required for the updation of the receiver filter when channel of the UOI changes.

If channel estimation and data detection are combined, a good amount of hardware/computations can be saved. The paper [15] discusses an integrated method for channel estimation and data detection and there, the effective signature code of the UOI is first determined as the intersection of the subspace spanned by the signature code of UOI (and its delayed versions) and received signal subspace. Once the effective signature code is obtained, the decorrelating detector or MMSE detector is formed using the subspace method as has been explained in Sec. 3.3.2. The drawbacks of this method are that, the channel estimation has to be done separately and when the channels of the interfering users change, the receiver filter has to be updated. Moreover errors in the estimation of the channel results in cancellation of the desired signal due to signature mismatch if MOE method is used directly.

In the proposed method the decorrelating or MMSE filters, corresponding to each path of the UOI is first determined in a blind, adaptive manner using the MOE criterion and the LMS algorithm. The received signal is then projected on to the subspace spanned by these filter vectors to obtain the final detector filter. By adopting differential encoding, performance matching the non-adaptive, non-blind MMSE receiver is obtained without explicitly estimating the channel, at a reasonable computational complexity.

5.2 SYSTEM MODEL

Some aspects of the system model are already presented in Sec. 3.3, however, important equations are reproduced in this section for easy reference. Consider, a base-band, synchronous direct sequence CDMA system with K active users. The received signals can be modeled as [15],

$$r(t) = s(t) + \sigma n(t) \tag{5.1}$$

where $n(t)$ is white, Gaussian noise with unit power spectral density, σ^2 is the variance of noise and $s(t)$ is the superposition of the data signals of K users, given by

$$s(t) = \sum_{k=1}^{K} A_k \sum_{n=-M}^{M} b_k(n) s_k(t - nT - \tau_k) \qquad (5.2)$$

where $2M + 1$ is the number of data symbols per user per frame, T is the symbol interval and $A_k, \tau_k, \{b_k(n); n = 0, \pm 1, ... \pm M\}$ and $\{s_k(t); 0 \le t \le T\}$ denote respectively, the received amplitude, delay, symbol stream, and normalized signalling waveform of the *k*th user. For the DS-CDMA multiple access format, the user signalling waveform are of the form

$$s_k(t) = \Sigma_{j=0}^{N-1} \beta_j^k \varphi(t - jT_c), \qquad t \in [0, T] \qquad (5.3)$$

where, N is the processing gain, $(\beta_0^k, \beta_1^k, ...\beta_{N-1}^k)$ is the signature sequence of $\pm 1s$ assigned to the *k*th *user*, φ is a normalized chip waveform of duration T_C, with $NT_C = T$.

It is assumed that $s_k(t)$ is supported only in the interval [0,T] and has unit energy and $b_k(n) \in \{-1, 1\}$ is the *n*th information bit of the *k*th user. Here binary phase shift keying (BPSK) modulated, data of the *k*th user is, spread by multiplying the data signal by the binary pseudorandom noise sequence. It will be assumed that the length of the pseudo noise (PN) sequence equals one symbol interval (short codes are assumed). Since CDMA systems based on IS-95 standard use long codes over many symbols, this model does not apply to these systems. However, future CDMA systems based on short codes have been proposed for the next generation systems, since they ease implementation of multiuser detectors.

In this work we restrict our attention to the synchronous CDMA, in which, $\tau_1 = \tau_2 = ...\tau_K = 0$. It is then sufficient to consider received signal during one symbol interval, and the received signal model becomes

$$r(t) = \Sigma_{k=1}^{K} A_k b_k s_k(t) + \sigma n(t), \qquad t \in [0, T] \tag{5.4}$$

At the receiver, chip matched filtering followed by chip rate sampling yields an N-vector of chip filter output samples, within a symbol interval T as shown,

$$\mathbf{r} = \Sigma_{k=1}^{K} A_k b_k \mathbf{s}_k + \sigma \mathbf{n} \tag{5.5}$$

where, $\mathbf{s}_k = 1/\sqrt{N}[\beta_0^k, \beta_1^k, \ldots\ldots\ldots\ldots\beta_{N-1}^k]^T$ is the normalized signature vector of the kth user, and $\mathbf{n}$ is a white Gaussian noise vector with mean zero and covariance matrix $\mathbf{I}_N$.

When the signal is transmitted over a multipath channel, at the receiver end, the effective signature waveform is the multichannel response to the original signature waveform. Suppose that K users are transmitting synchronously over a multipath channel, the number of resolvable paths for each user is $L = \lceil WT_m \rceil$ [15], where W is the signal bandwidth & T_m is the multipath spread of the channel. The impulse response of such a multipath channel for the kth user can be represented by a tapped delay line format:

$$h_k(t) = \Sigma_{l=1}^{L} h_{kl} \delta(t - (l - 1)T_c) \tag{5.6}$$

where $T_c = 1/W$, is the chip period and the coefficients h_{kl} are complex channel gains. The complex N-vector of chip matched filter output within a symbol interval is

$$\mathbf{r} = \Sigma_{k=1}^{K} A_k b_k \Sigma_{l=1}^{L} h_{kl} \mathbf{s}_{kl} + \sigma \mathbf{n} = \Sigma_{k=1}^{K} A_k b_k \tilde{\mathbf{s}}_k + \sigma \mathbf{n} \tag{5.7}$$

where, $\mathbf{s}_{kl}$ is the vector representation of the delayed user signature waveform, $s_k(t-(l-1)T_c)$ and $\tilde{\mathbf{s}}_k = \mathbf{S}_k \mathbf{h}_k$, is the received composite signature waveform of the kth user, where $\mathbf{S}_k = [\mathbf{s}_{k1} \mathbf{s}_{k2} \ldots\ldots\ldots\ldots \mathbf{s}_{kL}]$ and $\mathbf{h}_k = [h_{k1}\ h_{k2} \ldots\ldots\ldots h_{kL}]^T$

5.3 BLIND ADAPTIVE MULTIUSER DETECTION

5.3.1 Formation of path detectors

Single path case

Assume that the user of interest is the first user. A blind adaptive method for detecting the energy of the first user, using MOE-LMS method, is discussed first. It can be shown that this method ultimately converges to MMSE detector [9], and when noise is zero this becomes a decorelating detector. Here output variance is minimised using gradient descent algorithm as follows,

The output variance is minimised with respect to $\mathbf{x}_1$ where, $\mathbf{x}_1$ is a vector orthogonal to $\mathbf{s}_1$.

$$\mathrm{MOE}\ (\mathbf{x}_1) = E\ [(<\mathbf{r}, \mathbf{s}_1+\mathbf{x}_1>)^2] \tag{5.8}$$

the gradient of which lies in the same direction as the observed signal,

$$\nabla\ \mathrm{MOE} = 2 <\mathbf{r}, \mathbf{s}_1+\mathbf{x}_1> \mathbf{r} \tag{5.9}$$

The component orthogonal to $\mathbf{s}_1$ is a scaled version of the component of $\mathbf{r}$ orthogonal to $\mathbf{s}_1$ which is, $\mathbf{r}$-$<\mathbf{r}, \mathbf{s}_1> \mathbf{s}_1$. Therefore the projected gradient (orthogonal to $\mathbf{s}_1$) is,

$$2 <\mathbf{r}, \mathbf{s}_1+\mathbf{x}_1> [\mathbf{r}- <\mathbf{r}, \mathbf{s}_1> \mathbf{s}_1] \tag{5.10}$$

The adaptive algorithm updating proceeds at the data rate. Let us denote the responses of the matched filters for $\mathbf{s}_1$ and $\mathbf{s}_1+\mathbf{x}_1[n-1]$ by respectively,

$$z_{MF}[n] = < \mathbf{r}[n],\mathbf{s}_1 > \tag{5.11}$$

$$z[n] = < \mathbf{r}[n], \mathbf{s}_1+ \mathbf{x}_1[n-1]> \tag{5.12}$$

Stochastic gradient adaptation rule is then,

$$\mathbf{x}_1[n] = \mathbf{x}_1[n-1] - \mu\ z[n](\mathbf{r}[n]-Z_{MF}[n]\mathbf{s}_1) \tag{5.13}$$

where, μ is the step-size parameter. Finally MOE detector is given as, $\mathbf{m}_1 = \mathbf{s}_1 + \mathbf{x}_1$. When noise is zero, $\mathbf{m}_1 = \mathbf{d}_1$, the decorrelating detector. When noise is non-zero, $\mathbf{m}_1$ gives the MMSE detector.

Multipath case

In a multipath case the energies of individual paths cannot be recovered if we are proceeding as in the single path case because, the useful signal get cancelled when LMS algorithm is used [9, Sec. 6.6.2]. In that case we will have to minimise multiuser interference retaining the useful signal of the desired user. The gradient of the output energy is minimised along a direction orthogonal to the subspace spanned by the delayed signature waveform of the desired user, $S_1 = [s_{11}\, s_{12} \cdots s_{1L}]$. Therefore, the single user adaptive algorithm explained above can be modified to suit the multipath scenario as explained below.

The projected gradient orthogonal to $\mathbf{S}_1$ is,

$$2 < \boldsymbol{r}, \boldsymbol{s}_{11} + \boldsymbol{x}_{11} > [\boldsymbol{r} - \boldsymbol{P}_{S_1} \boldsymbol{r}] \tag{5.14}$$

where the projection matrix of $\mathbf{S}_1$, $\boldsymbol{P}_{S_1} = \boldsymbol{S}_1(\boldsymbol{S}_1^H \boldsymbol{S}_1)^{-1} \boldsymbol{S}_1^H$. Now,

$$\mathbf{x}_{11}(\mathrm{n}+1) = \mathbf{x}_{11}(\mathrm{n}) - \mu < \mathbf{r}(\mathrm{n}), \mathbf{s}_{11} + \mathbf{x}_{11} > [\mathbf{r}(\mathrm{n}) - \mathbf{P}_{S_1} \mathbf{r}(\mathrm{n})]. \tag{5.15}$$

Finally the MOE detector for the first path of the first user is given as, $\boldsymbol{m}_{11} = s_{11} + x_{11}$, where $\mathbf{x}_{11}$ is adaptive vector orthogonal to $\mathbf{s}_{11}$ and plays the same role of $\mathbf{x}_1$, seen in the single path case. Using identical steps, filter vectors of various paths of the desired user are obtained as,

$$\begin{aligned} \boldsymbol{m}_{11} &= \boldsymbol{s}_{11} + \boldsymbol{x}_{11} \\ \boldsymbol{m}_{12} &= \boldsymbol{s}_{12} + \boldsymbol{x}_{12} \\ &\cdots\cdots\cdots\cdots \\ \boldsymbol{m}_{1L} &= \boldsymbol{s}_{1L} + \boldsymbol{x}_{1L} \end{aligned} \tag{5.16}$$

Alternate method

The constrained receiver vectors $\{m_{1l}\}_{l=1}^{L}$ are obtained using the standard LMS algorithm applying minimum output energy (MOE) criterion [25]. The adaptive rule is briefly reviewed below. Denote the output energy of the lth arm of the RAKE as,

$$J_{MOE} = \mathbf{m}_{1l}^{H}\mathbf{R}\mathbf{m}_{1l} \tag{5.17}$$

where, $\mathbf{R}$ is the autocorrelation matrix of the received vector $\mathbf{r}$. Now J_{MOE} is minimised subject to the constraint, $\boldsymbol{S}_1^H \boldsymbol{m}_{1l} = \boldsymbol{S}_1^H \boldsymbol{s}_{1l}$. The gradient of the cost function is,

$$\nabla(J_{MOE}) = 2\mathbf{R}\mathbf{m}_{1l} \tag{5.18}$$

Approximating the autocorrelation matrix by the outer product of instantaneous received vector $\mathbf{r}$,

$$\nabla(J_{MOE}) = 2\mathbf{r}\mathbf{r}^{H}\mathbf{m}_{1l} \tag{5.19}$$

In order to restrict our search direction in the constrained subspace, we need to find the projection of the gradient on the subspace orthogonal to $\mathbf{S}_1$. Upon defining the orthogonal projection matrix, $\boldsymbol{P}_{S_1}^{\perp} = \boldsymbol{I} - \boldsymbol{S}_1\left(\boldsymbol{S}_1\boldsymbol{S}_1^H\right)^{-1}\boldsymbol{S}_1$, we arrive at the following recursive rule,

$$\mathbf{m}_{1l}(n+1) = \mathbf{m}_{1l}(n) - \mu\mathbf{P}_{\mathbf{S}_1}^{\perp}\mathbf{r}(n)\mathbf{r}(n)^{H}\mathbf{m}_{1l}(n) \tag{5.20}$$

where μ is the step-size parameter.

5.3.2 Formation of decorrelating detector

When SNR is high $\mathbf{m}_{11}$, $\mathbf{m}_{12}$......... $\mathbf{m}_{1L}$, each are orthogonal to the interfering users and so is any linear combination,

$\mathbf{m} = k_1\mathbf{m}_{11} + k_2\mathbf{m}_{12} + \cdots\cdots + k_L\mathbf{m}_{1L}$, where $\{k_l\}_{l=1}^{L}$, are constants. So it can be seen that when the received signal is correlated with $\mathbf{m}$, the interference from other users is totally removed and only the energy corresponding to the UOI survives.

Any linear combination of $\{\mathbf{m}_{1l}\}_{l=1}^{L}$ need not maximize the signal power. In order to maximize the signal power, the received signal is projected on to the subspace spanned by $\{\mathbf{m}_{1l}\}_{l=1}^{L}$ to get the final decorrelator. The same decorrelator $\mathbf{d}_1$ would be obtained if it is formed for the first user with the knowledge of channel parameters in a direct manner [15].

Proof

Let us confine our proof to a two-path case. The decorrelator corresponding to the first and second path of the first user is $\mathbf{d}_{11}$and $\mathbf{d}_{12}$. $\mathbf{d}_{11}$ is orthogonal to $\mathbf{s}_2$, $\mathbf{s}_3 \ldots\ldots \mathbf{s}_K$ subject to the constraint $\boldsymbol{S}_1^T\boldsymbol{d}_{11} = \boldsymbol{S}_1^T\boldsymbol{s}_{11}$. ie., $\mathbf{d}_{11}$ lies in the subspace of $\mathbf{s}_{11}$ and $\mathbf{s}_{12}$, which is orthogonal to the subspace spanned by $\mathbf{s}_2$, $\mathbf{s}_3 \ldots\ldots \mathbf{s}_K$. Similarly, $\mathbf{d}_{12}$ is orthogonal to $\mathbf{s}_2$, $\mathbf{s}_3 \ldots\ldots \mathbf{s}_K$ subject to the constraint $\boldsymbol{S}_1^T\boldsymbol{d}_{12} = \boldsymbol{S}_1^T\boldsymbol{s}_{12}$. ie., $\mathbf{d}_{12}$ lies in the space of $\mathbf{s}_{11}$ and $\mathbf{s}_{12}$ which is orthogonal to the subspace spanned by $\mathbf{s}_2$, $\mathbf{s}_3 \ldots\ldots \mathbf{s}_K$.

The decorrelator for the first user assuming exact channel knowledge and two multipaths [9] is

$$\begin{aligned}\mathbf{d}_1 &= [\mathbf{R}_c^{-1}]_{11}\mathbf{S}_1\mathbf{h}_1 + [\mathbf{R}_c^{-1}]_{12}\mathbf{s}_2 + \cdots\cdots [\mathbf{R}_c^{-1}]_{1K}\mathbf{s}_K \\ &= [\mathbf{R}_c^{-1}]_{11}\mathbf{s}_{11}\mathbf{h}_{11} + [\mathbf{R}_c^{-1}]_{11}\mathbf{s}_{12}\mathbf{h}_{12} + [\mathbf{R}_c^{-1}]_{12}\mathbf{s}_2 + \cdots\cdots [\mathbf{R}_c^{-1}]_{1K}\mathbf{s}_K\end{aligned} \tag{5.21}$$

$\boldsymbol{d}_1$ is orthogonal to the columns of $[\mathbf{s}_2\, \mathbf{s}_3 \cdots\cdots \mathbf{s}_K]$ and lies in the subspace spanned by the columns of $[\boldsymbol{s}_{11}\, \boldsymbol{s}_{12}\, \boldsymbol{s}_2\, \boldsymbol{s}_3 \cdots\cdots \boldsymbol{s}_K]$. Here $\mathbf{R}_c$ is the cross-correlation matrix of signature codes.

It can hence be concluded that d_1 lies in the space spanned by d_{11} and d_{12}. In general, $d_1^{'} = k_1 d_{11} + k_2 d_{12}$, lies in the space spanned by d_{11} and d_{12}, for any scalar k_1 and k_2. For some specific values of k_1 and k_2, $d_1^{'} = d_1$, and this is the vector closest to the received vector, **r** in the space spanned by d_{11} and d_{12}. Then it is enough we project the received vector **r**, on to the space spanned by d_{11} and d_{12}, to get a scaled version of d_1. As the magnitude scaling does not affect the performance, the projection can be used as the decorrelator.

5.3.3 Formation of MMSE detector

We know that the minimum variance detector subject to the constraint $\mathbf{S}_1^T \mathbf{m}_{mv} = \mathbf{g}$ is, $\mathbf{m}_{mv} = \mathbf{R}^{-1}\mathbf{S}_1(\mathbf{S}_1^T \mathbf{R}^{-1}\mathbf{S}_1)^{-1}\mathbf{g}$ [22], putting $g = g_1 = S_1^T s_{11}$, then $\mathbf{m}_{mv} = \mathbf{m}_{mv1}$, is nothing but the LMS detector for the first path of the first user, and is obtainable adaptively ie, $\mathbf{m}_{11} = \mathbf{m}_{mv1}$. Similarly, putting $g = g_2 = S_1^T s_{12}$, then $\mathbf{m}_{12} = \mathbf{m}_{mv2}$ is the LMS detector for the second path of the first user or

$$\mathbf{M}_1 \triangleq [\mathbf{m}_{11}\ \mathbf{m}_{12}] = [\mathbf{m}_{mv1}\ \mathbf{m}_{mv2}] = \mathbf{R}^{-1}\mathbf{S}_1(\mathbf{S}_1^T \mathbf{R}^{-1}\mathbf{S}_1)^{-1}\mathbf{G} \tag{5.22}$$

where $G = S_1^T S_1$. This shows that $\mathbf{R}^{-1}\mathbf{S}_1$ is in the subspace of M_1. But we know that MMSE detector, $m_{mse} = R^{-1} S_1 h_1$. In other words m_{mse} is in the space of M_1. So to get an MMSE-like detector it is enough we project the received vector **r** over the subspace spanned by $\{m_{1i}\}_{i=1}^{L}$ and the eigen vector of the covariance matrix of the projected signal will be a normalized version of the MMSE-like detector $\mathbf{m}_1$.

Proof

Let the projection matrix,

$$P = M_1(M_1^H M_1)^{-1} M_1^H \tag{5.23}$$

The projection of the received vector **r** over **P** is,

$$r_1 = Pr = M_1(M_1^H M_1)^{-1} M_1^H r \tag{5.24}$$

But from above we know that $\mathbf{M}_1$ and $W_1 \triangleq R^{-1} S_1$ lies in the same subspace. i.e., the projection $\mathbf{r}_1$ of **r** over $\mathbf{M}_1$ or W_1 will be identical. Now it is enough we show that the dominant eigen vector of $E(\mathbf{r}_1 \mathbf{r}_1^T)$, gives an MMSE-like solution. Subspace spanned by individual filters is, $W_1 = R^{-1} S_1$. Then the projection matrix,

$$P = W_1(W_1^T W_1)^{-1} W_1^T \tag{5.25}$$

The projection of the received vector **r** over **P** is,

$$r_1 = Pr = W_1(W_1^T W_1)^{-1} W_1^T r \tag{5.26}$$

Correlation matrix of the projected signal is,

$$\begin{aligned} \mathrm{E}(r_1 r_1^T) &= \mathrm{E}[P r (P r)^T] = \mathrm{E}[P r r^T P^T] = PRP^T \\ &= W_1(W_1^T W_1)^{-1} S_1^T R^{-1} R P^T \\ &= W_1(W_1^T W_1)^{-1} S_1^T W_1 (W_1^T W_1)^{-1} W_1^T \end{aligned} \tag{5.27}$$

Forming the Rayleigh quotient with $W_1 h$ we get,

$$\mathbf{h}^T \mathbf{W}_1^T \mathrm{E}(\mathbf{r}_1 \mathbf{r}_1^T) \mathbf{W}_1 \mathbf{h} \;\; = \mathbf{h}^T \mathbf{S}_1^T \mathbf{W}_1 \mathbf{h} \;\; = \mathbf{h}^T \mathbf{S}_1^T \mathbf{R}^{-1} \mathbf{S}_1 \mathbf{h} \tag{5.28}$$

Solution to this optimization problem is the minimum eigen vector of $\mathbf{S}_1^T \overset{-1}{\mathbf{R}} \mathbf{S}_1$ as in [20, equation (29) and (30)]. So it can be concluded that $\mathbf{m}_1$, the dominant eigen vector of $\mathrm{E}(\mathbf{r}_1 \mathbf{r}_1^T)$, will give an MMSE-like solution. In other words the eigen vector of the correlation matrix of the projected signal is MMSE-like detector up to a scaling factor.

5.4. INTEGRATED DATA DETECTION AND CHANNEL ESTIMATION

As has been shown, any linear combination of $\mathbf{m}_{11}$, $\mathbf{m}_{12}$.........$\mathbf{m}_{1L}$ will not guarantee maximum SNR. In order to maximize the signal power, the received signal is projected onto the subspace spanned by these filter vectors, and the dominant eigen vector of the correlation matrix of the projections, is computed to get the final filter $\mathbf{m}_1$. Thus in order to remove MAI the energy is minimized using the MOE criterion and after the removal of MAI the energy is maximized to improve the SNR. This max/min principle is applied here. The proposed receiver is neither dependent on estimated channel parameters nor on training sequences and hence the modulation format cannot be a plain BPSK. We thus assume differential encoding and decoding, implying that the information of the *n*th signalling interval is contained in the signal $b_1(n)$ and $b_1(n-1)$ where $b_1(n)$ and $b_1(n-1)$ are the bits of UOI in the *n*th and (*n*-1)th symbol interval, respectively. Thus, the decision rule is,

$$\hat{b}_1(n) = \mathrm{sgn}[\mathrm{Re}\{(\boldsymbol{m}_1^H \boldsymbol{r}(n))(\boldsymbol{m}_1^H \boldsymbol{r}(n-1)^*)\}] \tag{5.29}$$

where $\hat{b}_1(n)$ is the incremental phase between $b_1(n)$ and $b_1(n-1)$.

5.5 TEST SYSTEM AND SIMULATION RESULTS

The proposed receiver is simulated for four users (K = 4). The desired user has two paths (L = 2). The channel vector, $\mathbf{h}$ is assumed to be real and $\|\boldsymbol{h}\| = 1$. Processing gain of 31 (N = 31) is used. The interferers are at power levels 0 through 12 dBs. The step-size used for LMS algorithm is 0.001. Fig. 5.1 compares the BER of the proposed detector with ideal MMSE detector in a multipath non-fading channel when PN code is used as the signature code. Similarly Fig. 5.2 gives the performance when Gold code is the signature code.

At first the filter vector $\mathbf{m}_{11}$ corresponding to the first path of the first user is estimated in a blind adaptive manner using the MOE criterion, applying least mean square (LMS) algorithm. Even though the convergence rate of this algorithm is slower, the computational complexity is less compared to recursive least square (RLS) algorithm. It takes around 300 runs to attain convergence. After this, the filter vector $\mathbf{m}_{12}$ corresponding to the second path of the first user is estimated, adopting identical steps. The received signal vector $\mathbf{r}$ is now projected on to the subspace spanned by the filter vectors $\mathbf{m}_{11}$ and $\mathbf{m}_{12}$, the resulting vector $\mathbf{m}_{1,}$ will be free from interfering signals (Decorrelating detector) and large amplitude interferers (MMSE-like detector). At the same time energies of two paths of the first user are combined as done in a conventional RAKE receiver. MATHLAB program for the formation of the proposed detector is shown in Table 5.1.

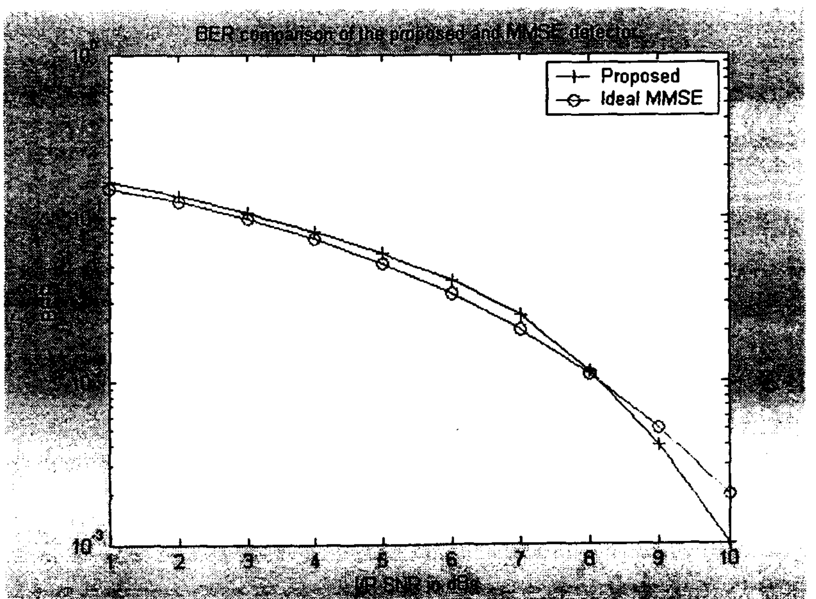

Fig. 5.1. BER comparison of proposed receiver and ideal MMSE receiver when PN sequence is used as the signature code

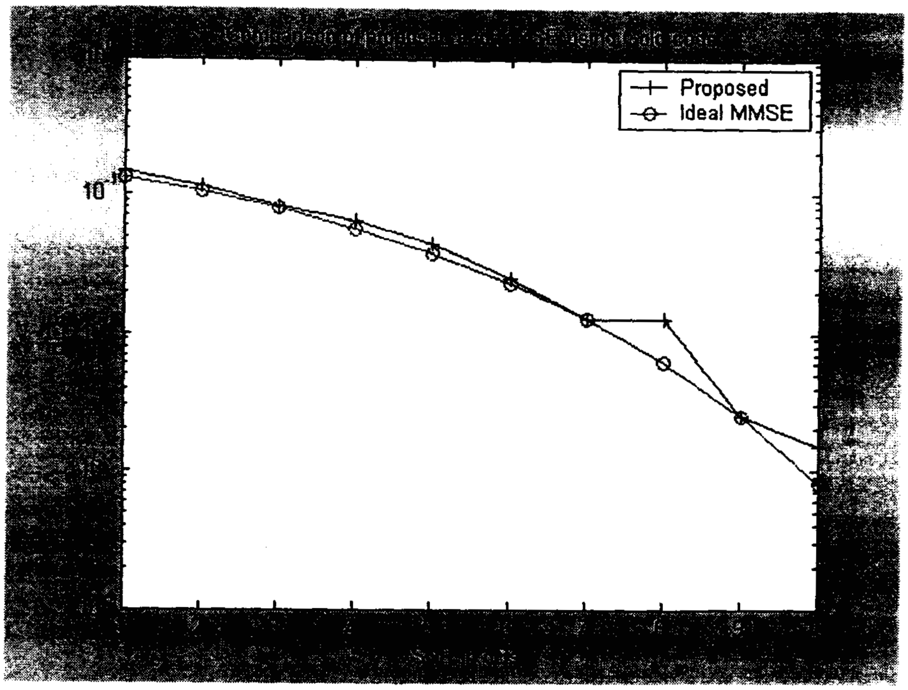

Fig. 5.2 BER comparison of proposed receiver and ideal MMSE receiver when Gold sequence is used as the signature code

Table 5.1 MATLAB program for the formation of the proposed detector

```
% Get the PN codes and scale it; desired user with one multipath
% and three interferers with single path assumed
    a = pn_code/sqrt(31);a1 = 3*a(1,:);a2 = 4*a(2,:);a5 = a(5,:);
    a3 = a(3,:);a4 = a(4,:);A = [a3;a4]';
% Set the sequences to be transmitted assuming some channel parameters
% for the desired user
    x =0.6;t = x*a3+sqrt(1-x^2)*a4;t = t/norm(t);p = [a1;a2;a5;t];
% Initialize matrices, set the step-size of the LMS algorithm,
% noise value etc.
    c3 = zeros(1,31);c4 = zeros(1,31);cr1 = zeros(31,31);
```

```
q =0.001;d1 = 1;u1 = a3';ni = 1;
```

% Iteratively get path detectors

```
for n = 1:2000
```

% Form the transmitted bits

```
d = sign(randn(1,4));d2(n) = d(4);
```

% Form the transmitted sequence corrupted by noise

```
r = d*p+ni*randn(1,31);
```

% Get the component orthogonal to the codes of the desired user

```
x = pinv(A)*r';

ort = r'-A*x;
```

% Adjust c3 so that orthogonal component is minimised

```
z1 = (a3+c3)*r';

c3 = c3-q*z1*ort';
```

% Repeat the same for second path

```
z2 = (a4+c4)*r';

c4 = c4-q*z2*ort';
```

% Finally get path detectors ec3 and ec4

```
ec3 = a3+c3;

ec4 = a4+c4;
```

% Get the projection of the received signal over the path detectors

```
A1 = [ec3; ec4]';

x1 = pinv(A1)*r';b1 = A1*x1;
```

% Find the dominant eigen vector of the projections

% using rank-one PASTd algorithm

```
  y = u1'*b1;
  d1 = 0.97*d1+y^2;
  e = b1-u1*y;
  u1 = u1+e*y/d1;
end
```

% u1 is the proposed detector

5.6 CONCLUSION

In this chapter the proposed blind, adaptive detector, which can be analytically proved to be an MMSE-like detector, is discussed. The performance of this detector was validated by simulation and was found to be on par with an ideal MMSE detector. In a multipath scenario, the energies of different paths are efficiently combined without explicitly estimating the channel parameters. This receiver was implemented using MOE-LMS algorithm. The computational complexity of this receiver is very low compared with subspace based and MOE-RLS based receivers. The performance of this receiver in a fading channel is found to be encouraging. In the following chapter we compare the performance of the proposed receiver with competing methods.

Chapter 6

COMPARISON OF THE PROPOSED DETECTOR WITH COMPETING METHODS

6.1 INTRODUCTION

In this chapter we compare the performance of the proposed method with subspace method and RLS version of the MOE method, in terms of computational complexity, convergence rate, BER and correlation coefficient.

6.2 SINGLE PATH CASE

6.2.1 Comparison with subspace method

Blind multiuser detectors (Decorrelating and MMSE) were developed with prior knowledge of signature waveform and timing of the user of interest applying subspace techniques in [15]. A blind adaptive method, based on signal subspace tracking is also introduced therein. It is shown in [15, 26] that compared with MOE-RLS method of complexity $O(N^2)$, the subspace method offers lower computational complexity O(NK) (where N is the processing gain and K is the number active users in the channel) and better performance in terms of the steady-state signal-to-interference ratio (SIR) and is robust against waveform mismatch.

However, the computational complexity of the proposed method (MOE-LMS) is only of the order of O(N) per iteration [27] in a single path system in contrast to O(NK) of the subspace method. The reduced computational complexity is useful for adaptive detector implementations in a time varying channel or in a dynamic channel where the user scenario changes frequently. When used in a multipath environment, the subspace method faces another problem. In this case, channel estimation also has to be performed separately and then used for data detection along with the obtained subspace components [15]. In contrast, our method performs channel estimation and data detection in an integrated fashion.

Comparison in terms of correlation coefficient

Fig. 6.1 compares the correlation coefficient and convergence rate of the proposed method and the subspace-based method for single path channel when implemented adaptively. Here the processing gain, N=31. There are 6 users including the desired user. The interferers are at power levels of 6 through 20 dB. The signature sequences of the users are PN sequences. The signal-to-noise ratio is 10 dB

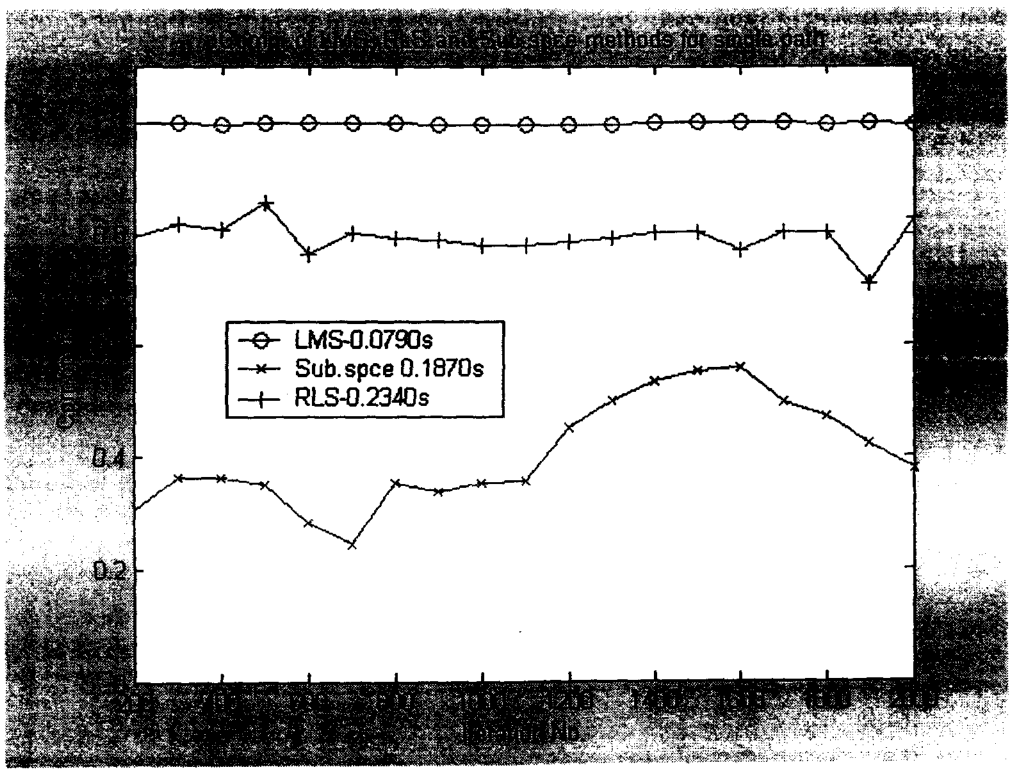

Fig. 6.1. Correlation coefficient and complexity comparison of RLS, LMS and subspace methods

The subspace-tracking algorithm used is the PASTd algorithm [15]. In the subspace-tracking algorithm, the forgetting factor λ is 0.995. A scaled version of the MMSE detector is computed from the formula $\boldsymbol{m}_s = \boldsymbol{U}_s\Lambda_s^{-1}\boldsymbol{U}_s^T\boldsymbol{s}_1$ [15], where $\mathbf{U}_s$ is the matrix containing eigen vectors of the signal subspace as its columns, Λ_s is the diagonal matrix whose diagonal elements are the corresponding eigen values. The computation of the detector is done at the intervals of 100 iterations, as is clear from the figure. Then the normalized correlation coefficient ρ, between the obtained filter $\mathbf{m}_s$ and the ideal MMSE filter $\mathbf{m}_{mse}$ is computed as,

$$\rho = \frac{\left|\boldsymbol{m}_s^H \boldsymbol{m}_{mse}\right|}{\left\|\boldsymbol{m}_s\right\|\left\|\boldsymbol{m}_{mse}\right\|} \tag{6.1}$$

The correlation coefficient so computed is plotted against the iteration number in Fig. 6.1. Now the MMSE-like filter is obtained as explained earlier, using proposed method as $\boldsymbol{m}$. Then as in the case of subspace method, the correlation coefficient is computed and plotted in the Fig. 6.1. It can be verified from the figure that the performance of the subspace method is inferior to the proposed method. Moreover the computational complexity of the subspace method is high compared to the proposed MOE-LMS algorithm. The subspace method takes 0.1870 seconds while the LMS algorithm takes only 0.0790 seconds for 2000 iterations.

BER comparison

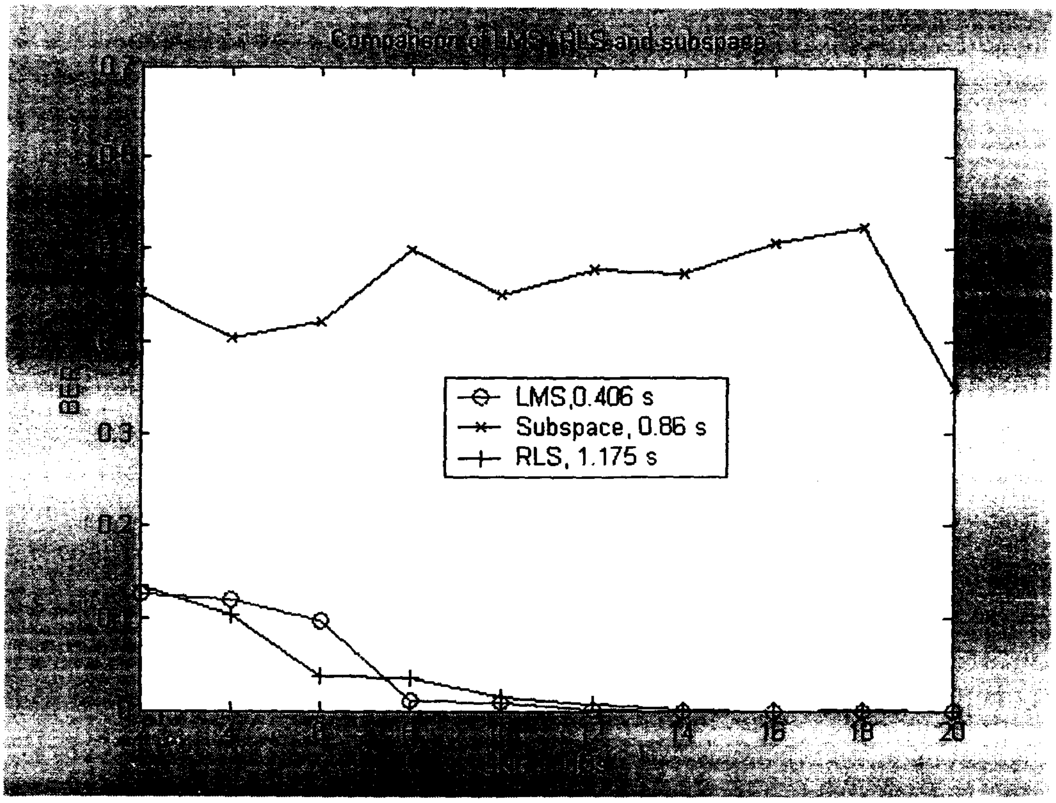

Fig. 6.2 BER and complexity comparison for LMS, subspace and RLS methods using adaptive methods in a single-path scenario

Performance is also compared in terms of the BER as shown in Fig. 6.2. No. of users, K=6. PN code of length 31 is used. Time taken for 10,000 iterations is shown. BER calculated is for 1000 runs. SNR is varied from 2 dB to 20 dB in steps of two. BER comparison also shows the supremacy of the proposed method over subspace and RLS methods. BER of the subspace method is very high while the computational complexity is reasonable.

6.2.2 Comparison with RLS method

Recursive least square (RLS) algorithm for adaptive implementation of the blind linear MMSE detector was explained in Sec.3.2.1.2. Fig. 6.1 and 6.2 also compares the performance of RLS algorithm with the proposed method. It can be seen from the figures that the computational complexity of RLS method is more than that of subspace and LMS methods. The performance (correlation coefficient and BER) is also inferior to LMS method.

6.3 MULTIPATH CASE-COMPARISON WITH BUZZI'S METHOD

A timing-free blind multiuser detector is presented in [23] and is explained in Sec. 3.6 of the thesis. An adaptive version of this detector is given in later sections of [28]. The extension of RLS algorithm to multipath channels is explained there. The paper actually deals with a timing-free (where the timing and channel impulse response of the UOI are unknown but spreading code is known), asynchronous version of the blind multiuser detector. In our comparison the above work is adapted to a synchronous channel where the timing and signature code of UOI are known.

Adaptive implementations

The batch estimation procedure given in Sec. 3.6 is applicable only when the scenario is stationary on a long-term basis, i.e., when the covariance properties of the observables may be considered constant for sufficiently long time intervals. In a dynamic scenario, it is always desirable to have recursive or adaptive methods.

The first step to derive an adaptive algorithm is to devise a tracking procedure for the blocking matrix **D** [Sec.3.6]. Starting on a set of observables, **r**(1),........**r**(n) say, an estimate $\hat{\mathbf{D}}$(n) of the blocking matrix **D** can be obtained through the following exponentially weighted counterpart of the minimization problem,

$$\sum_{i=1}^{n}\lambda^{n-i}\left\|\hat{\mathbf{D}}(n)^{H}\mathbf{r}(i)\right\|^{2}\text{such that, }\mathrm{Diag}(\hat{\mathbf{D}}(n)^{H}\mathbf{S}_{1})=\beta=[\beta_{1},\beta_{2}\cdots\cdots\beta_{(N+1)P}]^{T} \quad (6.2)$$

where λ is the forgetting factor. Applying, the standard Lagrangian techniques, we obtain the updating algorithm,

$$\hat{\mathbf{D}}(n) = \frac{1}{\lambda}\left[\hat{\mathbf{D}}(n-1) - \mathbf{p}(n)\mathbf{r}^{H}(n)\hat{\mathbf{D}}(n-1)\right] \tag{6.3}$$

where $\mathbf{k}(n)$is the following Kalman filter gain,

$$\mathbf{k}(n) = \frac{\mathbf{R}^{-1}(n-1)\mathbf{r}(n)}{\lambda + \mathbf{r}(n)^{H}\mathbf{R}^{-1}(n-1)\mathbf{r}(n)} \tag{6.4}$$

and $\mathbf{R}(n)$ is the exponentially weighted sample covariance matrix of the observables

$$\mathbf{R}(n) = \sum_{i=1}^{n} \lambda^{n-i}\mathbf{r}(i)\mathbf{r}^{H}(i) \tag{6.5}$$

The cascade of the blocking matrix $\mathbf{D}$ and the whitening filter amounts to multiplying the data by $\mathbf{U}_D^H$, where $\mathbf{U}_D$ is the matrix containing on its columns the (N+1)P dominant eigenvectors of $\mathbf{DD}^H$. On the other hand, these eigenvectors form an orthonormal basis for $R(\mathbf{D})$, and may be efficiently tracked by generating data whose covariance matrix is $\mathbf{DD}^H$ and passing them on to a subspace-tracking algorithm. We are thus left with an estimate, $\hat{\mathbf{U}}_D(n)$ say, of $\mathbf{U}_D$, where by the whitened data, $\mathbf{y}_w(n) = \hat{\mathbf{U}}_D(n)\mathbf{r}(n)$ can be formed and finally forwarded to a subspace tracking algorithm to track the principal eigenvector, $\hat{\mathbf{v}}(n)$ say, of the covariance matrix.

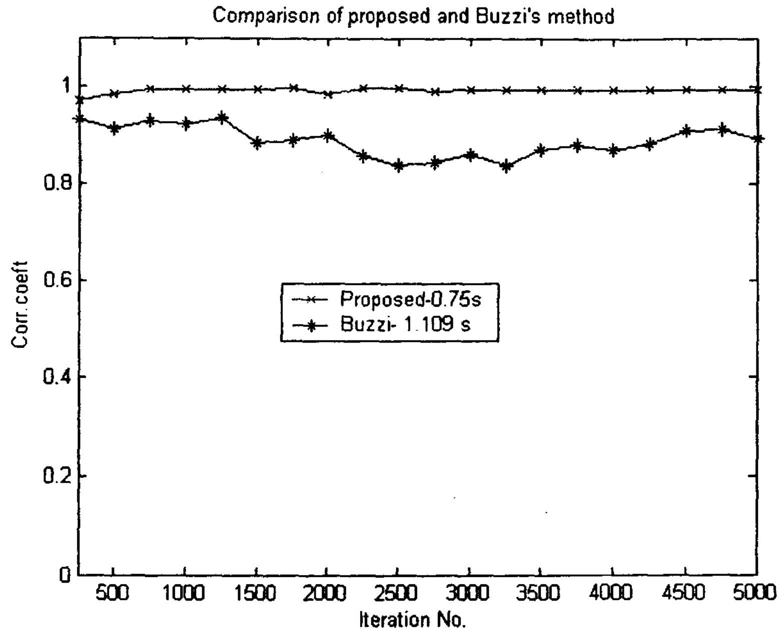

Fig. 6.3. Comparison of proposed and Buzzi's method

The estimate of the vector **m**, can thus be obtained as

$$\hat{\mathbf{m}}(n) = \hat{\mathbf{U}}_D(n)\hat{\mathbf{v}}(n) \tag{6.6}$$

The above algorithm (Buzzi's method) was implemented and compared with our method as shown in Fig. 6.3. Here also performance of the Buzzi's method and the proposed method is compared in terms of correlation coefficient relative to the optimal MMSE receiver. The normalized correlation coefficient ρ, between the obtained filter using Buzzi's method, $\mathbf{m}_b$ and the ideal MMSE filter $\mathbf{m}_{mse}$ is computed as, $\rho = \frac{|\mathbf{m}_b^H \mathbf{m}_{mse}|}{\|\mathbf{m}_b\|\|\mathbf{m}_{mse}\|}$ [28]. The correlation coefficient is computed at the intervals of 250 iterations and is plotted against the iteration number as shown in figure. Similarly the correlation coefficient for the proposed method also is computed relative to the optimal MMSE filter. This also is plotted against the number of iteration in Fig. 6.3. The processing gain is 31. The signature code used is PN-sequence. There are three interferes at power levels 0, 9.5 and 12 dBs. The signal-to-noise ratio is 6 dB. The number of paths for UOI, L=2. The forgetting factor used for the adaptive RLS algorithm is 0.95 and the step size for LMS algorithm, μ=0.001.

It can be seen from the figure that the computational complexity of the RLS method (Buzzi's method) is higher than that of our method. Moreover the performance (measured in terms of correlation coefficient) is only around 0.8, compared to unity of the proposed method. Additionally, the performance is not stabilizing in the case of RLS algorithm.

BER comparison

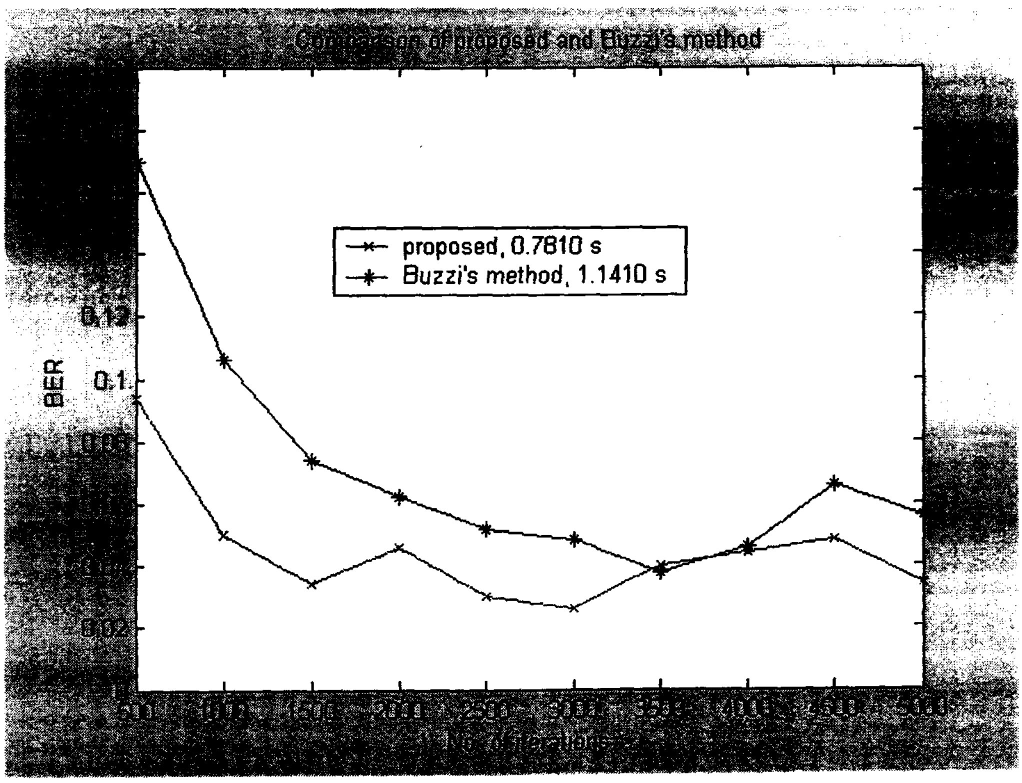

Fig. 6.4 BER and complexity comparison

The performance of the proposed method and the Buzzi,s method is also compared in terms of the BER. In the simulation, shown in Fig. 6.4, No. of users, K = 4; No. of paths for the desired user, L=2; SNR=6 dB; Gold code of length 31 is used. Time taken for 5000 iterations is shown. This comparison also highlights the merits of the proposed scheme.

6.4 CONCLUSION

In this chapter we compared the performance of the proposed receiver with the existing receivers. Performance criteria used are correlation coefficient/BER and computational complexity. Single-path receivers were first implemented using subspace tracking algorithm and RLS algorithm. Our detector was found to outperform these detectors in terms of computational complexity and correlation coefficient matching. An adaptive, blind detector suitable for multipath channels was also implemented using Buzzi's method and compared with our method. Here also our method was found to excel Buzzi's method. In the following chapter we discuss the performance of the proposed detector in fading multipath channels.

Chapter 7

PERFORMANCE OF THE PROPOSED DETECTOR IN FADING MULTIPATH CHANNELS

7.1 INTRODUCTION

So far we were concerned with CDMA systems in an AWGN channel (frequency non-selective) or a linear filter channel with AWGN (frequency selective channel). In this chapter the performance of the detector in a fading channel is considered. The mobile channel is usually modeled as a fading (time-varying) frequency selective channel. The time variant, impulse responses of these channels are a consequence of the constantly changing physical characteristics of the media. It can be seen that a severe penalty in SNR is to be paid as a consequence of the fading characteristics of the channel.

7.2 CHARACTERISTICS OF FADING MULTIPATH CHANNELS

If we transmit an extremely short pulse over a time-varying multipath channel, the received signal might appear as a train of pulses. Hence, one characteristic of a multipath medium is the time spread introduced in the signal that is transmitted through the channel. A second characteristic is due to the time variations in the structure of medium. As a result of such time variations, the nature of multipath varies with time. That is, if we repeat the pulse sounding experiment over and over, we shall observe changes in the received pulse train, which will include changes in the sizes of individual pulses, changes the relative delays among the pulses, and sometimes, changes in the number of pulses observed in the received pulse train. Moreover, the time variations appear to be unpredictable to the user of the channel.

Consider the transmission of an unmodulated carrier at frequency f_c. The low-pass equivalent of the received signal [29],

$$\begin{aligned} r(t) &= \sum_l \alpha_l(t) \bar{e}^{j2\pi f_c \tau_l(t)} \\ &= \sum_l \alpha_l(t) e^{-j\theta_l(t)} \end{aligned} \tag{7.1}$$

where, l - Number of multipaths

$\tau_l(t)$ - time variant propagation delay of the lth path

$\theta_l(t) = 2\pi f_c \tau_l(t)$

$\alpha_l(t)$ – the time varying attenuation factor of the lth path.

Thus the received signal consists of the sum of a number of time-variant vectors (phasors) having amplitudes $\alpha_l(t)$ and phases $\theta_l(t)$. Note that large dynamic changes in the medium are required for $\alpha_l(t)$ to change sufficiently to cause a significant change in the received signal. On the other-hand, $\theta_l(t)$ will change by 2π radians whenever τ_l changes by $1/f_c$. But $1/f_c$ is a small number and hence θ_l change by 2π radians with relatively small motions of the medium. We also expect the delays $\tau_l(t)$ associated with different signals paths to change at different rates and in an unpredictable (random) manner. This implies that the received signal $r(t)$ can be modelled as a random process.

The multipath propagation model for the channel embodied, in the received signal $r(t)$, results in signal fading. The fading phenomenon is primarily a result of the time variations in the phases $\{\theta_l(t)\}$. That is, the randomly time variant phases

$\{\theta_l(t)\}$ associated with the vectors $\{\alpha_l(t)e^{-j\theta_l}\}$ at times results in the vectors adding destructively. When that occurs, the resultant received signal $r(t)$ is very small or practically zero. At other times, the vectors $\{\alpha_l(t)e^{-j\theta_l}\}$ add constructively so that the received signal is large. Thus the amplitude variations in the received signal, termed signal fading, are due to the time variant multipath characteristics of the channel. When the equivalent low pass impulse response,

$$h(\tau;t) = \sum_l \alpha_l(t)\bar{e}^{j\theta_l(t)}\ \delta(\tau - \tau_l(t)) \tag{7.2}$$

is modeled as a zero-mean complex valued gaussian process, the envelope $|h(\tau;t)|$ at any instant, t is Rayleigh distributed. In this case the channel is said to be a Rayleigh fading channel. In the event that there are fixed scatterers or signal reflectors, $h(\tau;t)$ can no longer be modeled as having zero mean. In this case, the envelope $|h(\tau;t)|$ has a Rice distribution and the channel is said to be a Rician fading channel. Another probability distribution function that has been used to model the envelope of fading signal is the Nakagami m-distribution.

7.3 PARAMETERS OF INTEREST

Autocorrelation function

The auto correlation function,

$$\phi_c(\tau) = \phi_c(\tau_1 - \tau_2) = 1/2\, E[h^*(\tau_1;t)h(\tau_2;t)] \tag{7.3}$$

is simply the average power output of the channel as a function of the time delay τ. For this reason, $\varphi_c(\tau)$ is called the multipath intensity profile or the delay power spectrum of the channel. The range of values of τ over which $\varphi_c(\tau)$ is essentially non zero is called the multipath spread of the channel and is denoted by T_m.

A completely analogous characterization of the time-variant multipath channel begins in the frequency domain. By taking the Fourier transform of $h(\tau; t)$ we obtain the time–variant transfer function $h(f; t)$ where f is the frequency variable. Thus,

$$h(f;t) = \int_{-\infty}^{\infty} h(\tau;t)\, e^{-j2\pi f\tau} d\tau \tag{7.4}$$

Similarly the autocorrelation function in frequency domain can be defined as,

$$\varphi_c(\Delta f) = \int_{-\infty}^{\infty} \varphi_c(\tau) e^{-j2\pi\Delta f\tau} d\tau . \tag{7.5}$$

Since $\varphi_c(\Delta f)$ is an autocorrelation function in the frequency variable, it provides us with a measure of the frequency coherence of the channel.

Coherence bandwidth

As a result of the Fourier transform relationship between $\varphi_c(\Delta f)$ and $\varphi_c(\tau)$, the reciprocal of the multipath spread is a measure of the coherence bandwidth of the channel. That is,

$$(\Delta f)_c \approx \frac{1}{T_m} \tag{7.6}$$

where $(\Delta f)_c$ denotes the coherence bandwidth. Thus, two sinusoids with frequency separation greater than $(\Delta f)_c$ are affected differently by the channel.

Frequency selective and non-selective channel

If $(\Delta f)_c$ is small in comparison with the bandwidth of the transmitted signal, the channel is said to be frequency selective. In this case, the signal is severely distorted by the channel. On the other hand, if $(\Delta f)_c$ is large in comparison with the bandwidth of the transmitted signal, the channel is said to be frequency non-selective.

Coherence time and Doppler spread

We now focus our attention on the time variations of the channel as measured by the parameter Δt in $\varphi_c(\Delta f\, ;\, (\Delta t))$. In order to relate the Doppler effects to the time variations of the channel, we define the Fourier transform of $\varphi_c(\Delta f\, ;\, (\Delta t))$ with respect to the variable, Δt to be the function $S_c(\Delta f\, ;\, \lambda)$. That is,

$$S_c(\Delta f;\lambda) = \int_{-\infty}^{\infty} \varphi_c(\Delta f;\Delta t) e^{-j2\pi\lambda\Delta t} d\Delta t \tag{7.7}$$

with Δf set to zero and $S_c(0;\lambda) \equiv S_c(\lambda)$, the relation in (7.7) becomes,

$$S_c(\lambda) = \int_{-\infty}^{\infty} \varphi_c(\Delta t) e^{-j2\pi\lambda\Delta t} d\Delta t \tag{7.8}$$

The function $S_c(\lambda)$ is a power spectrum that gives the signal intensity as a function of the Doppler frequency λ. Hence, we call $S_c(\lambda)$ the Doppler power spectrum of the channel. The range of values of λ over which $S_c(\lambda)$ is essentially non-zero is called the Doppler spread B_d of the channel. Since $S_c(\lambda)$ is related to $\varphi_c(\Delta t)$ by the Fourier transform, the reciprocal of B_d is a measure of the coherence time of the channel. That is,

$$(\Delta t)_c \approx \frac{1}{B_d} \tag{7.9}$$

where, $(\Delta t)_c$ denotes the coherence time. Clearly, a slowly changing channel has a large coherence time or equivalently, a small Doppler spread.

7.4 THE EFFECT OF SIGNAL CHARACTERISTICS ON THE CHOICE OF A CHANNEL MODEL

Now consider the effect of the signal characteristics on the selection of a channel model that is appropriate for the specified signal. Thus, let $s(t)$ be the equivalent low pass signal transmitted over the channel and let $s(f)$ denote its frequency content. Then the equivalent low pass received signal, exclusive of additive noise, may be expressed either, in terms of the time domain function, $h(\tau;t)$ and $s(t)$ as

$$r(t)= \int_{-\infty}^{\infty} h(\tau;t)\, s(t-\tau)\; d\tau. \tag{7.10}$$

or in terms of the frequency functions $h(f;t)$ and $s(f)$ as,

$$r(f)= \int_{-\infty}^{\infty} h(f;t)\, s(f)\; e^{j2\pi f t}\; df. \tag{7.11}$$

Suppose we are transmitting digital information over the channel by modulating the basic pulse $s(t)$ at a rate 1/T where T is the signalling interval. It is apparent from the above equation that the time variant channel characterized by the transfer function $h(f;t)$ distorts the signal $s(f)$. If $s(f)$ has a bandwidth W greater than coherence band width $(\Delta f)_c$ of the channel, $s(f)$ is subjected to different gains and phase shifts across the band. In such a case the channel is said to be frequency selective. Additional distortion is caused by the time variations in $h(f;t)$. This type of distortion is evidenced as variations in the received signal strength, and has been termed as fading. It should be emphasized that the frequency selectivity and fading are viewed as two different types of distortion. The former depends on the multipath spread or, equivalently, on the coherence bandwidth relative to signal bandwidth W. The latter depends on the time variations of the channel, which are grossly characterized by the coherence time $(\Delta t)_c$ or equivalently, the Doppler spread B_d.

The effect of the channel on the transmitted signal $s(t)$ is a function of our choice of signal bandwidth and signal duration. For example, if we select the signalling interval T to satisfy the condition $T>>T_m$, the channel introduces a negligible amount of inter symbol interference. If the bandwidth of the signal pulse $s(t)$ is $W\approx 1/T$, the condition $T>>T_m$, implies that, $W << \frac{1}{T_m} \approx (\Delta f)_c$.

That is, the signal bandwidth W is much smaller than the coherence bandwidth of the channel. Hence, the channel is frequency non-selective. In this case we say that the multipath components in the received signal are not resolvable, because $W<< (\Delta f)_c$. The transfer function h(0;t) for a frequency non-selective channel may be expressed in the form,

$$h(0;t) = \alpha(t)\bar{e}^{j\varphi(t)} \tag{7.12}$$

Where $\alpha(t)$ represents the envelope and $\varphi(t)$ represents the phase of the equivalent low-pass channel. When this is modeled as a zero-mean complex valued gaussian random-process, the envelope $\alpha(t)$ is Rayleigh distributed for any fixed value of t and

$\varphi(t)$ is uniformly distributed over the interval $(-\pi,\pi)$. Either of the channel parameters $(\Delta t)_c$ or B_d can be used to characterise the rapidity of fading.

7.5 MOBILE CHANNEL

In built-up urban areas, fading occurs because the height of the mobile antennas are well below the height of the surrounding structures, so there is no single line-of-sight to the base station. Even when a line of sight exists, multipath still occurs due to reflections from the ground and surrounding structures. The incoming radio waves arrive from different directions with different propagations delays. The signal received by the mobile at any point in space may consist of a large number of plane waves having randomly distributed amplitudes, phases and angles of arrival. These multipath components combine vectorially at the receiver antenna and cause the signal received by the mobile to distort or fade. Even when a mobile receiver is stationary, the received signal may fade due to the movement of surrounding objects in the radio channel. If objects in the radio channel are static, and motion is considered to be only due to that of the mobile, then fading is purely a spatial phenomenon. The spatial variations of the resulting signal are, seen as temporal variations by the receiver as it moves through the multipath field. Due to the constructive and destructive effects of multipath waves arriving at various points in space, a receiver moving at high speed can pass through several fades in a small period of time.

Doppler shift

Due to the relative motion between the mobile and the base station, each multipath wave experiences an apparent shift in frequency. The shift in received signal frequency due to motion is called the Doppler shift and is directly proportional to the velocity and direction of motion of the mobile with respect to the direction of arrival of the received signal. Doppler shift frequency $f_D = \frac{v_m}{\lambda_c} \cos\theta$ [30], where v_m is the velocity of the mobile, λ_c the wavelength of the carrier and θ the spatial angle between the direction of motion of the mobile and the direction of arrival of the wave. It can be seen from the equation that, if the mobile is moving toward the direction of arrival of the wave, the Doppler shift is positive (i.e., the apparent received frequency is increased), and if the mobile is moving away form the direction of arrival of the wave, the Doppler shift is negative (i.e., the apparent received frequency is decreased).

Factors influencing fading

- Multipath propagation:

  The presence of reflecting objects and scatterers in the channel creates a constantly changing environment that dissipates the signal energy in amplitude, phase and time.

- Speed of the Mobile:

  The relative motion between the base station and the mobile results in random frequency modulation due to different Doppler shifts on each of the multipath components.

- Speed of surrounding objects:

  If objects in the radio channel are in motion, they induce a time varying Doppler shift on multipath components.

- The transmission bandwidth of the signal:

If the signal bandwidth is greater than the coherence bandwidth of the multipath channel, the received signal will be distorted.

7.6 SIMULATION OF FADING CHANNEL

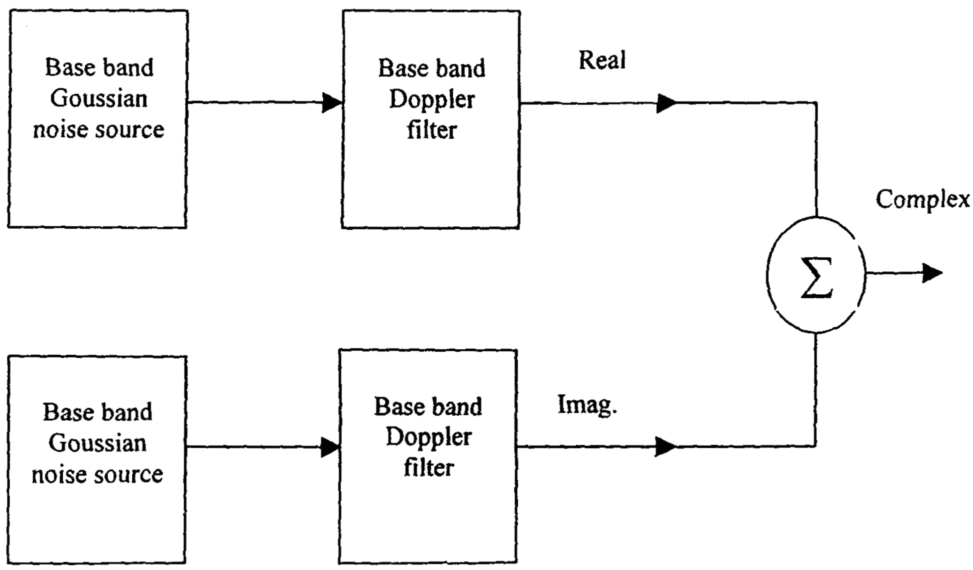

Fig. 7.1 Rayleigh fade base-band simulator

The fading channel is simulated according to the Clarke's model [31]. A popular simulation method uses [30], the concept of in-phase and quadrature modulation paths to produce a simulated signal. This is known as Rayleigh fade base-band simulator. As shown in Fig. 7.1, two independent Gaussian, low-pass noise sources are used to produce in-phase and quadrature fading branches. Complex gaussian source, may be formed by summing two independent gaussian random variables, which are orthogonal (i.e., $g = a + jb$, where a and b are real gaussian random variables and g is complex gaussian). A MATLAB program to simulate Rayleigh faded mobile channel is given in Table 7.1.

7.7 PERFORMANCE EVALUATION OF THE PROPOSED METHOD IN FADING CAHNNEL

7.7.1 Constant amplitude time-varying phase channel

In the simulations PN sequences of length 31 are used. Number of users including the desired user is four. User 1 is assumed to be the desired user and has the unit energy $A_1^2=1$. Number of paths for the first user is 2. The three interfering users are operating at 0, 21.97 and 27.73 dBs relative to the desired user. The SNR (A_1^2/σ^2) is varied from o to 10 dBs. The step-size of the LMS algorithm is, 0.001. The channel coefficient of the desired user is generated by passing noise sequences through two identical 2nd-order Butterwprth filter with a normalized bandwidth of 0.0001. The norm of the generated channel parameters is made unity by normalization.

The individual filters corresponding to two paths are first obtained using LMS algorithm as already explained earlier. Then the received signal is projected onto the subspace spanned by these individual filters and the principal eigen vector of the projected signals is formed using rank-one PASTd algorithm to get the MMSE-like detector in the fading channel. The forgetting factor used in the PASTd algorithm [15] is 0.97.

The performance of the proposed detector is compared with that of an ideal MMSE detector used in an identical non-fading channel. The performance comparison is shown Fig. 7.2. The performance of a non-adaptive MMSE detector used in the same fading channel also is shown. It can be seen that the non-adaptive

MMSE detector totally fails in fading channel. We have also shown single user channel performance for comparison.

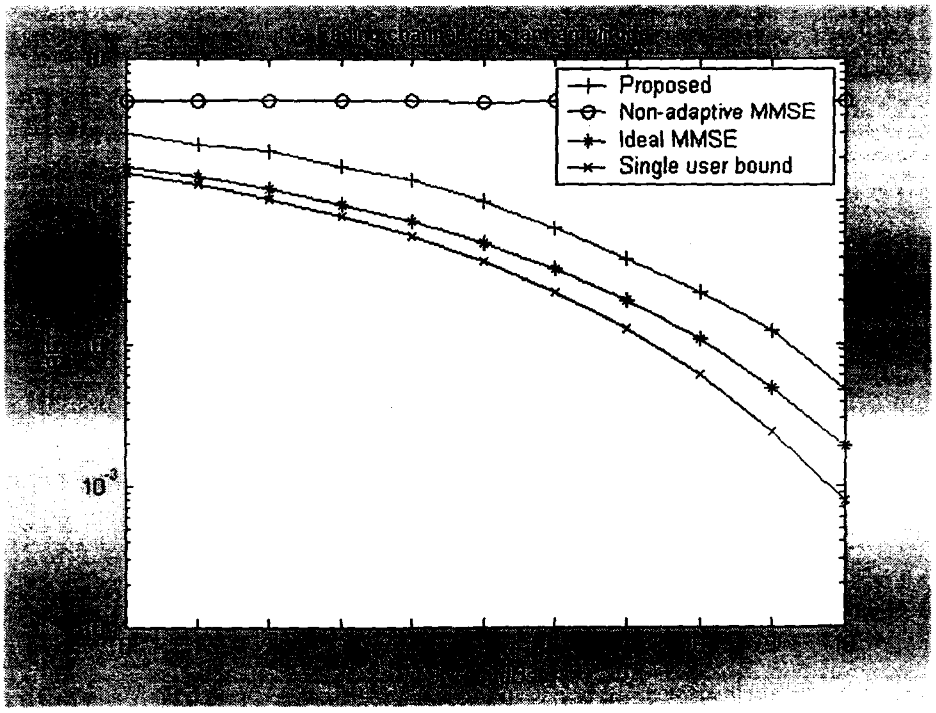

Fig. 7.2. Performance of the proposed method in a constant amplitude, varying phase fading channel

7.7.2 Rayliegh fading channel

In this simulation also there are four users including the desired user. But the three interfering users are operating at 0 dB each, relative to the desired user. Other system details are as in the constant amplitude simulation, as explained above. But in this case the envelope of the channel parameters are Rayleigh distributed and phase is uniformly distributed. That is, in this case amplitude of the channel also is time varying.

The Rayleigh fading process $\{h_{kl}(n)\}$ is generated by filtering two independent real gaussian processes with two identical 2^{nd} order Butterworth filters.

The 3db bandwidth f_D of the filter normalized to the symbol rate 1/T is used as a measure of fading rate. The normalized bandwidth of the Butterworth filter is selected as $f_DT = 10^{-2}$. This corresponds to a fast fading channel [32]. The symbol rate 1/T is set to 10kbps. The Doppler shift f_D considered is 100 H_z which corresponds to a mobile speed of 60 Km/hr at a carrier frequency of $1.8GH_Z$. The channel model used for the desired user (first user) is the two-path frequency selective channel [33],

$$h(t) = 0.8e^{j\varphi 0}\,\delta(t) + 0.6e^{j\phi 1}\,\delta(t - Tc) \tag{7.13}$$

Where the envelope of each path is Rayleigh distributed with rms values 0.8 & 0.6. The phases ϕ_0 and ϕ_1 are uniformly distributed. Note that total power in the two multipaths is normalized to unity because $0.8^2 + 0.6^2 = 1$. Simulation results are shown in Fig. 7.3.

In the case of Rayleigh fading channel also it can be seen that a non-adaptive detector fails miserably. But the proposed detector is able to follow the ideal MMSE detector to some extent. The performance of the proposed detector in the Rayleigh channel is inferior to that in the constant amplitude channel because of the additional amplitude variation experienced by the Rayleigh channel.

Table 7.1 MATLAB program to simulate Rayleigh faded mobile channel

```
% Form the Doppler low pass filter
    [b5, a9] = butter(2,.001);
% Feed the Gaussian random variables to the filter
    r1 = randn(1,10000);r2 = randn(1,10000);
    y1 = filter(b5,a9,r1);y2 = filter(b5,a9,r2);
```

% Form the channel parameters for the first path

```
z1 = y1+y2*i;
```

% Normalize the channel parameters

```
z1abs = sum(abs(z1))/10000;z1 =0.8*z1/z1abs;
```

% Repeat the same for the second path

```
r1 = randn(1,10000);r2 = randn(1,10000);
y1 = filter(b5,a9,r1);y2 = filter(b5,a9,r2);
z2 = y1+y2*i;z2abs = sum(abs(z2))/10000;z2 = 0.6*z2/z2abs;
```

% Store the channel parameters as a complex array

```
yc = [z1;z2];
```


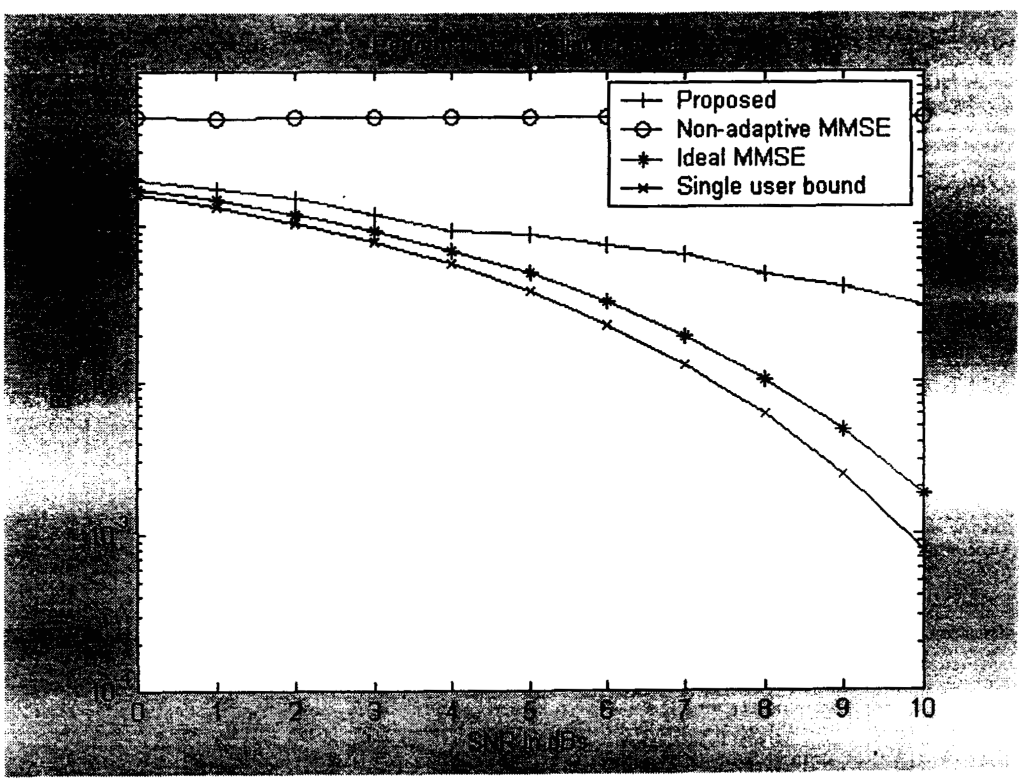

Fig. 7.3 Performance comparison of the proposed method in a Rayleigh fading channel

7.8 CONCLUSION

The performance of the proposed detector in fading multipath channels is presented in this chapter. First the proposed detector is tested in constant amplitude, time-varying phase channel. The detector also is then tested in a Rayleigh fading channel where the channel coefficients are complex and its envelope (amplitude) as well phase fluctuates. The performance of the detector in the two fading channels was compared with an ideal MMSE detector operating in an identical channel but without fading. Performance in this case is not much different from an ideal MMSE detector. It is also compared with a non-adaptive MMSE receiver operating in the same fading channel. It can be seen that the non-adaptive receiver fails miserably in a fading channel whereas the performance of our receiver is much better. In the following chapter we propose a new method for channel estimation in CDMA channels.

Chapter 8

UNBIASED BLIND CHANNEL ESTIMATION SCHEME FOR MULTIPATH CDMA SYSTEMS

8.1 INTRODUCTION

A blind, unbiased, adaptive method for channel estimation in multipath CDMA channels is presented. This work is a by-product of the blind, adaptive multiuser detection already developed for multipath CDMA channels. Usually the estimated channel parameters are biased due to the presence of multiple access interference (MAI), multipath interference (MPI) and noise. In this work we are able to demonstrate a channel estimation scheme, which is accurate and unbiased.

The availability of perfect channel estimation scheme is very crucial for a multiuser detector in a multipath CDMA system. In the conventional multipath CDMA receivers, matched filters are configured corresponding to different paths of the desired user. The data can be detected by combining the energies in different paths using RAKE receiver, provided the gains of each path is known. Channel estimates are usually affected by the presence of interfering users and interfering paths, because the interfering codes are in general non-orthogonal. The conventional method for channel estimation is the moving average of pilot symbols, using the input or output signal of the adaptive filter. The paper [34] discusses an unbiased channel estimation scheme based on the constrained minimum mean-squared error (CMMSE) criterion for frequency non-selective channels. The above technique is extended to frequency selective channels in [35]. But such a receiver suffers from

MPI, which again causes a bias in the channel estimate. In an attempt to remove such a bias, constrained MMSE-RAKE receiver that employs an unbiased maximum-likelihood (ML) channel estimator is proposed in [35] and its performance is analysed. But this method is computationally rigorous and non-adaptive.

The proposed channel estimation scheme is suited to dynamic channels as it is adaptive, it is computationally efficient and does not require any training sequences or the knowledge of the codes of the interfering users (blind). The minimum output energy (MOE) filters corresponding to different paths of the desired user are first obtained in an adaptive manner using the LMS algorithm. In the first method proposed, the received signal is projected onto the subspace spanned by the obtained filters and subsequently de-noised to get the MMSE-like filter of the desired user. Then using standard expressions, the biased or approximate channel coefficients are computed. In the second method the filters corresponding to different paths are modified to make it MPI free too. Then the received signal is projected along these modified filters to get an unbiased, accurate channel estimate.

8.2 PROPOSED TECHNIQUE

In the basic constrained MMSE (CMMSE) receiver [35], the channel is estimated by exploiting pilot symbols under the assumption that $\{h_{1l}\}_{l=1}^{L}$ are quasi-constant. If a pilot symbol is inserted at every Q_p symbol, then the channel estimate is given by,

$$h_{1l}(n) = \frac{1}{N_p}\sum_{i=0}^{N_p-1} d^*((v-i)Q_p)\boldsymbol{m}_{1l}^H((v-i)Q_p)\mathbf{r}((v-i)Q_p) \tag{8.1}$$

where, $v = \lfloor (n/Q_p) \rfloor$, $d((v-i)Q_p)$ is the pilot symbol and N_p is a positive integer. It is shown in [35] that the channel estimate obtained above is biased, in a multipath scenario and a method to redress the bias is given therein.

We are suggesting a different technique to get rid of bias in channel estimation. To get an approximate, biased channel estimate, let us assume that the obtained $\{\boldsymbol{m}_{1l}\}_{l=1}^{L}$, completely removes MAI. In that case, the projection of $\mathbf{S}_1\mathbf{h}_1$ on the subspace spanned by $\boldsymbol{M}_1 = [\boldsymbol{m}_{11}\, \boldsymbol{m}_{12} \cdots\cdots \boldsymbol{m}_{1L}]$ approximately corresponds to the MMSE detector [28], i.e.,

$$\boldsymbol{M}_1(\boldsymbol{M}_1^H \boldsymbol{M}_1)^{-1} \boldsymbol{M}_1^H \mathbf{S}_1 \mathbf{h}_1 \approx \boldsymbol{m}_1 \tag{8.2}$$

From above, we can compute MAI free, channel parameter $\mathbf{h}_1$ as we know other parameters. To get a rigorous unbiased channel estimate let us define,

$$\boldsymbol{O}_1 = \boldsymbol{M}_1(\boldsymbol{S}_1^H \boldsymbol{S}_1)^{-1} \tag{8.3}$$

In this case it can be shown that $\mathbf{O}_{1l}^H \mathbf{s}_{1l'} = 0$ for $l \neq l'$. So we have transformed filter matrix $\mathbf{M}_1$ to $\mathbf{O}_1$, to make it MPI free too. We have already made them approximately MAI free, by using MOE criterion. Now to get the unbiased channel estimate, we project the received vector $\mathbf{r}$, along $\boldsymbol{O}_1 = \{\boldsymbol{o}_{1l}\}_{l=1}^{L}$ and average it over a sufficiently large number of data samples. The obtained average will be the channel estimate along the respective paths, provided we use differential encoding and decoding in the system. Both adaptive and non-adaptive schemes are implemented.

8.3. SIMULATION RESULTS

Fig. 8.1 gives the results of non-adaptive (theoretical) implementations. First MMSE filter is computed directly from the expression $\boldsymbol{m}_1 = \mathbf{R}^{-1}\mathbf{S}_1\boldsymbol{h}_1$. Then we obtained the filter vectors, corresponding to different paths of the desired user using the expression $\boldsymbol{W}_1 = \boldsymbol{R}^{-1}\boldsymbol{S}_1$, assuming that the signature codes of all users and their amplitudes. As we have already established that $\mathbf{M}_1$ and $\boldsymbol{W}_1$ lie in the same subspace we can immediately write,

$$\mathbf{W}_1(\mathbf{W}_1^T\mathbf{W}_1)^{-1}\mathbf{W}_1^T\boldsymbol{S}_1\boldsymbol{h}_1 \approx \boldsymbol{m}_1 \tag{8.4}$$

from which we can calculate approximate values of channel estimate, $\hat{\boldsymbol{h}}_1$. The normalized correlation coefficient [28], $\rho = \frac{\|\hat{\mathbf{h}}_1^H\mathbf{h}_1\|}{\|\hat{\mathbf{h}}_1\|\|\mathbf{h}_1\|}$, is now computed and plotted against different multipath correlations (correlation of the desired user's signal along different paths). As can be seen from the figure, there is a wide variation in the channel correlation coefficient when multipath correlation changes. We also computed the exact values of the channel parameters from the expression, $\mathbf{R}^{-1}\mathbf{S}_1\boldsymbol{h}_1 = \boldsymbol{m}_1$. The corresponding correlation coefficient is also shown in Fig. 8.1 for comparison. As is clear from the figure, the usage of exact expression is giving an unbiased channel estimate. The estimate in this case is free from MPI. For the simulation, number of users K = 4, number of paths of the desired user L = 2, length of the PN code N = 31.

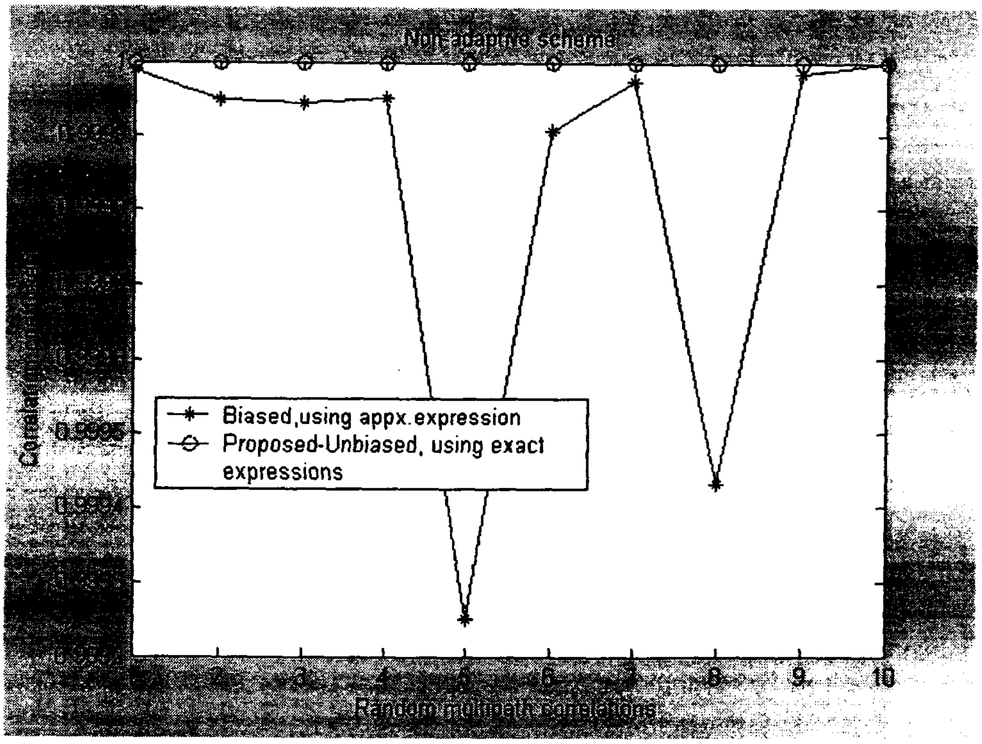

Fig. 8.1 Non-adaptive, un-biased channel estimation

An adaptive (practical) implementation is shown in Fig. 8.2. In the biased method of the adaptive implementation, the channel is estimated from the obtained filter $\mathbf{m}_1$ as explained in the initial portions of Sec. 8.2. The normalized correlation coefficient, ρ is plotted against different multipath correlations as shown in figure. From the figure it can be seen that the channel estimation is biased and depends on MPI. In the adaptive, unbiased method channel is estimated by using the averaging method as explained in the later portions of Sec. 8.2. We could have very well calculated the MMSE-like filter m_1 and auto correlation matrigx **R** adaptively and then used the expression $\mathbf{m}_1 \approx \mathbf{R}^{-1}\mathbf{S}_1\mathbf{h}_1$, to get channel estimate. But it is seen that computation of both $\mathbf{m}_1$ and **R** adaptively and the use of approximate expression above gives inaccurate results. This justifies the adoption of averaging technique to get an unbiased channel estimate adaptively. For the simulation, number of users

K=4, number of paths of the desired user L=2, length of the PN code N=31, number of iterations to get reasonable results 10000.

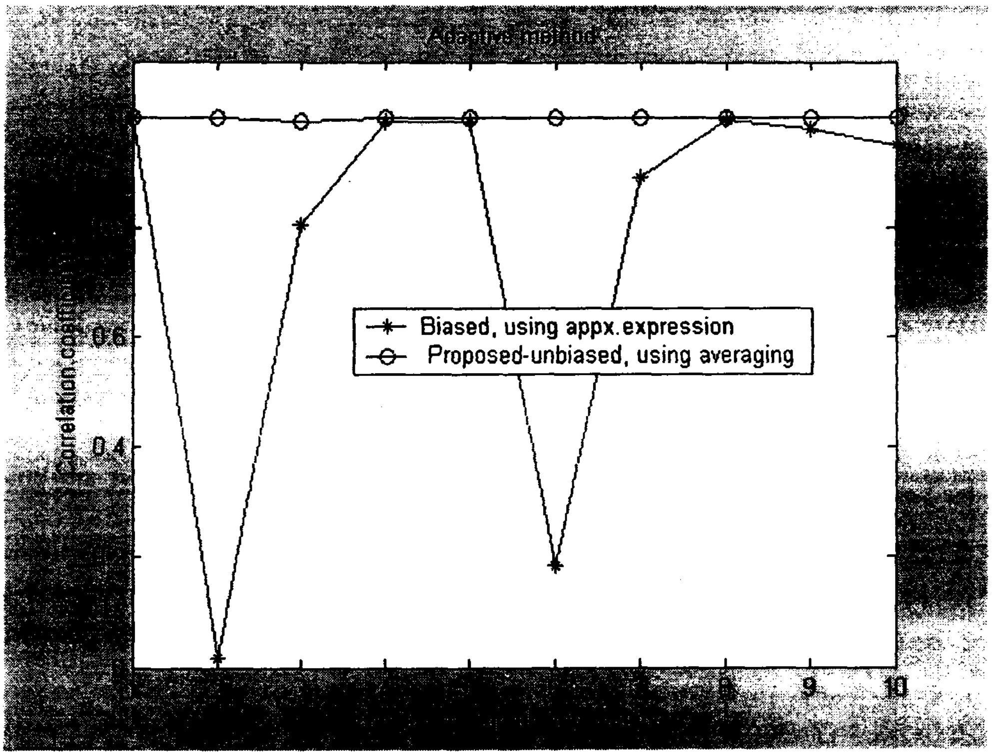

Fig. 8.2 Adaptive, unbiased channel estimation

8.4 CONCLUSION

A biased and unbiased channel estimation scheme for multipath CDMA channels is introduced. The main attraction of this work is the presentation of an adaptive, blind method for channel estimation, which requires only the signature code and timing of the desired user. The channel estimation is found to be close to the theoretical values in the unbiased, non-adaptive method. In the unbiased, adaptive method the performance measured in terms correlation coefficient differs only nominally from the actual values. In the next chapter we discuss some related works, which are the offshoots of the main research work.

Chapter 9

RELATED MINOR WORKS

In this chapter we discuss some miscellaneous works, which are the by-products of the main research work.

9.1 ADAPTIVE DECORRELATOR

One important out-come of our main work is the realization that a decorrelator (decorrelating detector) can be obtained adaptively when noise is zero which is impossible using other methods (Sec. 5.3.2). This inability is illustrated in the case of RLS method as shown below. As in [26], a recursive procedure for updating the filter $\mathbf{m}(n)$ can be obtained as follows,

$$\mathbf{k}(n) \triangleq \frac{\mathbf{R}^{-1}(n-1)\mathbf{r}(n)}{\lambda + \mathbf{r}^{T}(n)\mathbf{R}^{-1}(n-1)\mathbf{r}(n)} \tag{9.1}$$

$$\mathbf{h}(n) \triangleq \mathbf{R}^{-1}(n)\mathbf{s} = \frac{1}{\lambda}\left[\mathbf{h}(n-1) - \mathbf{k}(n)\mathbf{r}^{T}(n)\mathbf{h}(n-1)\right] \tag{9.2}$$

$$\mathbf{m}(\mathrm{n}) = \frac{1}{\mathbf{s}^{\mathrm{T}}\mathbf{h}(\mathrm{n})}\mathbf{h}(\mathrm{n}) \tag{9.3}$$

$$\mathbf{R}^{-1}(\mathrm{n}) = \frac{1}{\lambda}\left[\mathbf{R}^{-1}(\mathrm{n}-1) - \mathbf{k}(\mathrm{n})\mathbf{r}^{\mathrm{T}}(\mathrm{n})\mathbf{R}^{-1}(\mathrm{n}-1)\right] \tag{9.4}$$

where, $\mathbf{R}(n) \triangleq \sum_{i=1}^{n} \lambda^{n-i}\mathbf{r}(i)\mathbf{r}^{T}(i)$.

The recursive updation of $\mathbf{R}^{-1}(\mathrm{n})$ will work only when that matrix is of full rank. This matrix is rank deficient when the number of users is less than the processing gain and the noise is zero. But in the case of our method, the proposed detector will converge to a decorrelator in a noiseless situation even when the system is under-loaded (number of users less than the processing gain). It may be noted that the adaptive decorrelator [15] that can be configured using subspace method in a noiseless under-loaded scenario, however has higher complexity than the complexity of our detector

The problem due to formation of a rank deficient matrix in a noiseless scenario is also stated in [23]. The paper discusses a pathological situation of useful signal cancellation, when the channel is noise-free. There the interference cancellation matrix **D** is given by [23, equation (16)],

$$\mathbf{D} = \mathbf{R}^{-1}\mathbf{S}_1\left[\left(\mathbf{S}_1^H\mathbf{R}^{-1}\mathbf{S}_1\right)\otimes \mathbf{I}_{NM+1}\right]^{-1} \text{x diag}\left(\beta_1,\dots\dots\dots,\beta_{MN+1}\right) \tag{9.5}$$

As noise reduces to zero, it is stated that the columns of matrix **D** become orthogonal to the useful signature $\mathbf{S}_1\mathbf{h}_1$, which is thus completely nullified by the blocking matrix. The remedy stated there is the addition of external noise to make the covariance matrix non-singular. The above pathological situation is not at all arising in our method, as we are not performing inversion of the covariance matrix. Thus our method is effective even when noise is zero and works without additional complexity.

9.2 FADING-FREE DECORRELATOR

We were able to configure fading-free decorrelators using the MOE-LMS algorithm, when noise is assumed to be zero. We can obtain decorrelators corresponding to each path of the desired user using the MOE-LMS algorithm. Let $\mathbf{d}_{11},\mathbf{d}_{12},\dots\dots\dots\mathbf{d}_{1L}$ are the decorrelating detectors corresponding to L paths of the UOI. But according to [15],

$$\mathbf{d}_{11} = \sum_{i=1}^{KL} \left[\mathbf{R}_c^{-1}\right]_{1i} \mathbf{s}_i \tag{9.6}$$

Where $\{\mathbf{s}_i\}_{i=1}^{KL}$, are the signature codes of the users and its delayed replicas, and $\mathbf{R}_c$ is the cross correlation matrix of $\{\mathbf{s}_i\}_{i=1}^{KL}$ and $\left[\mathbf{R}_c^{-1}\right]_{1i}$ represents the *i*th element in the first row of $\mathbf{R}_c^{-1}$. Now suppose we take any linear combination of $\{\mathbf{d}_{1\ell}\}_{l=1}^{L}$ and form the inner product with any signature code or its delayed replica $\mathbf{s}_j$, as shown,

$$\left[k_1 \mathbf{d}_{11} + \ldots\ldots. k_L \mathbf{d}_{1L}\right]^T \mathbf{s}_j$$

$$= k_1 \sum_{i=1}^{KL} \left[\mathbf{R}_c^{-1}\right]_{1i} \mathbf{s}_i^T \mathbf{s}_j + \ldots k_L \sum_{i=1}^{KL} \left[\mathbf{R}_c^{-1}\right]_{Li} \mathbf{s}_i^T \mathbf{s}_j$$

$$= k_1 \sum_{i=1}^{KL} \left[\mathbf{R}_c^{-1}\right]_{1i} \left[\mathbf{R}_c\right]_{ij} + \ldots k_L \sum_{i=1}^{KL} \left[\mathbf{R}_c^{-1}\right]_{Li} \left[\mathbf{R}_c\right]_{ij}$$

$$= k_1[\mathbf{R}_c^{-1}\,\mathbf{R}_c]_{1j} + \ldots\ldots\ldots\ldots\ldots\ldots k_L[\mathbf{R}_c^{-1}\,\mathbf{R}_c]_{Lj}$$

$$= \begin{cases} k_j, \text{for } 1 \le j \le L \\ 0, \text{ for } L+1 \le j \le KL \end{cases} \tag{9.7}$$

where, $\{k\}_{l=1}^{L}$ are constants and the integer j varies from 1 to KL. Each filter vector obtained as above is orthogonal to the interfering subspace as well as delayed replicas of the desired user and so is linear combination of the above filters.

The aforesaid property can be advantageously used in a fading channel. Once the filter of the desired user is orthogonal to the codes of the interfering users and their delayed replicas, any change in the channel parameters of the interfering users is not going to contribute any additional interference to the user of interest and any change in the channel parameters of the UOI will change only the optimum filter choice, but will not disrupt the data detection. This is validated in Fig. 9.1.

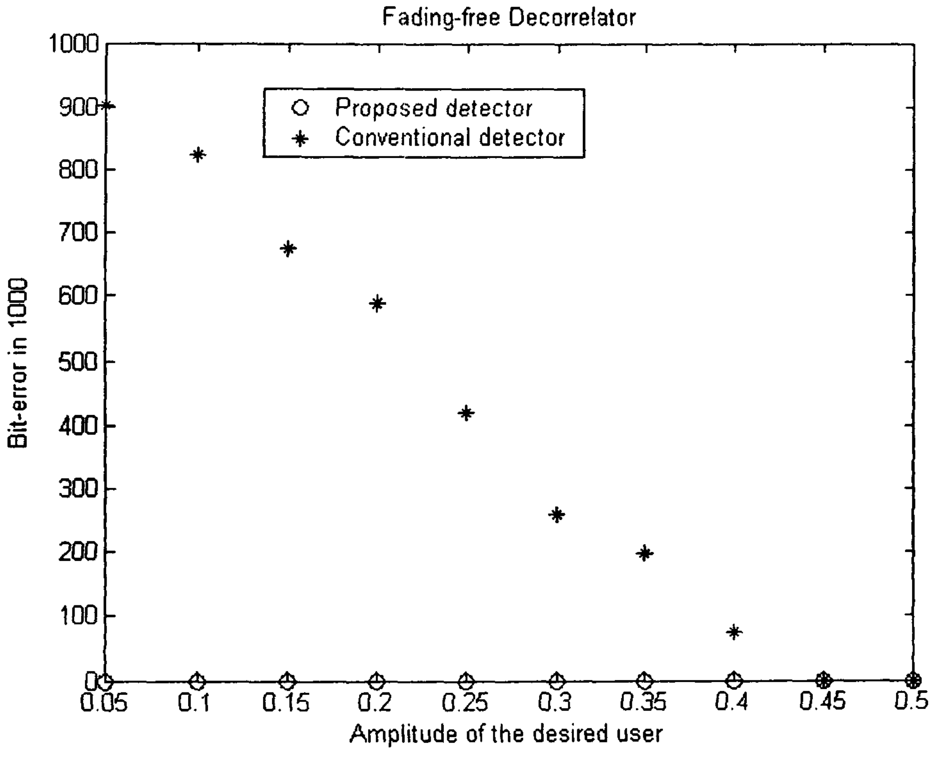

Fig. 9.1. Fading-free decorelator

Here we have one desired user and two interfering users. Each interfering user takes two paths while the desired user takes a single path. The length of the code is eight. The channel parameters of the interfering users are time-varying and vary from symbol to symbol. Bit error performance of the system when a filter matched to the signature code of the desired user (conventional detector) is first simulated for different amplitudes of the desired user as is shown in the graph. Then we formed the decorrelator, which is orthogonal to interfering users and their delayed replicas. Now even if the channel parameters change, the decorrelator formed will be still orthogonal to interfering users and their delayed replicas. In this case the bit error will be theoretically zero. But as we have obtained the decorrelator using MOE-LMS algorithm, this will not be perfectly orthogonal to the interfering signals and hence a non-zero bit error at lower amplitudes of desired user is observed.

9.3 ROBUST BLIND DETECTION UNDER SIGNAL MISMATCH

The proposed detector can be used as a robust blind detector under signal mismatch. The conventional MOE detector is very sensitive to signal mismatch and channel distortions and does not perform satisfactorily in the presence of multipath propagation. The signal mismatch problem was treated in [20] using constrained optimisation approach by forcing the receiver response to all delayed copies of the signal of interest to zero. The constraints alleviate the signal cancellation due to mismatch, however these methods do not exploit the signal energy that is contained in the delayed copies of the signal of interest and, therefore do not offer optimal performance. An improvement was proposed where the constraint values are optimised by a max/min approach rather than set to one or zero in [22]. The performance of this method tends to be close that of the optimal MMSE receiver at high signal-to-noise ratio (SNR) in the presence of multipath. However, the complexity is higher due to the use of eigen value decompositions.

The proposed detector can be used as a blind detector under the above scenario. Let us assume that the user of interest is the first user. The constrained receiver vectors $\{\mathbf{m}_{1l}\}_{l=1}^{L}$ are obtained using the standard LMS algorithm applying minimum output energy (MOE) as already explained in chapter 5. If we are interested only in the single-path energy we can use one of the vectors from the set $\{\mathbf{m}_{1l}\}_{l=1}^{L}$ as the filter to tap energy along the concerned path. In this case, though the SNR is affected there is no question of signal mismatch. In the multipath case a proper linear combination of $\{\mathbf{m}_{1l}\}_{l=1}^{L}$ is likely to maximize the SNR of the desired user. In order to maximize the SNR, the received signal $\mathbf{r}(n)$ is projected on the subspace spanned by the filter these vectors, to get the projection vector $\hat{\mathbf{r}}_1(n)$. The dominant eigen vector of the projection matrix is then computed as already explained to get the detector which will remove the signal mismatch problem. The performance of various detectors in this connection is shown in Fig. 9.2. Here, no. of users is 3 and no. of paths for the first user is 2.

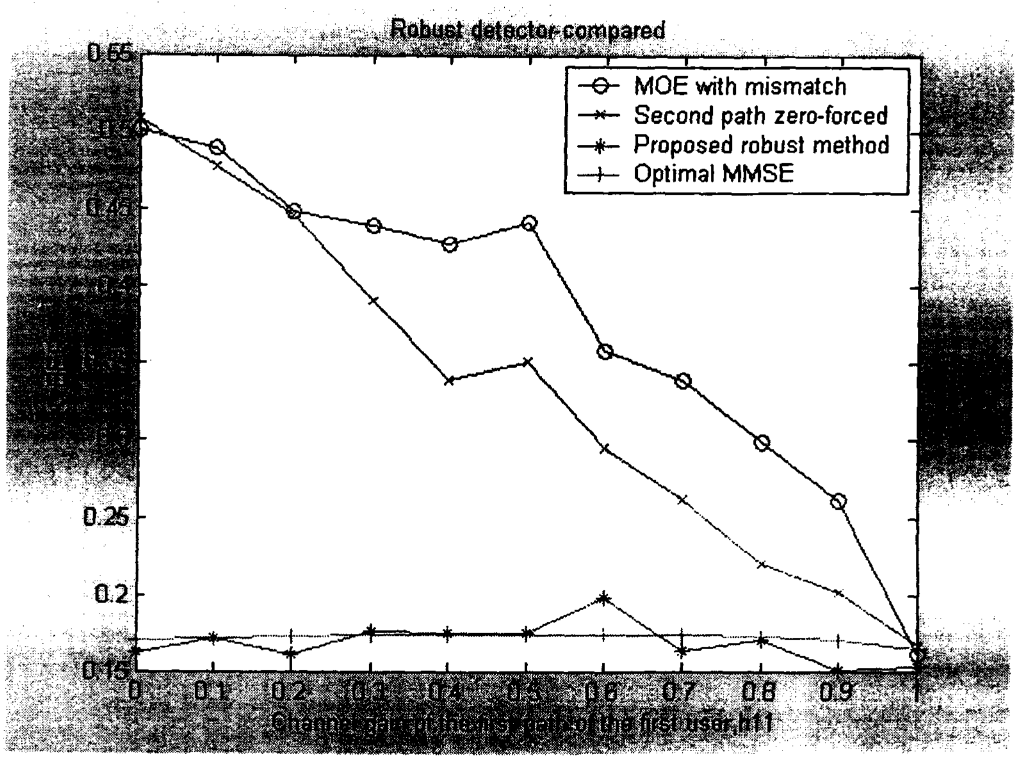

Fig. 9.2 Robust detector

9.4 NOVEL SCHEME FOR ENHANCING CAPACITY

In the third generation wide-band CDMA mobile systems [1], orthogonal codes are proposed in the down-link (forward link) as well as in the up-link (reverse link). The simplicity of detection process and the elimination of MAI are the major attractions of a synchronous system using orthogonal codes. But this is not free from problems. In a conventional CDMA system using PN sequences, the numbers of users are soft limited, where as in an orthogonal system the number of users is hard limited.

A novel method for enhancing the capacity [37] of a mobile communication system, which uses orthogonal codes, is proposed here. In this scheme the codes are divided into different groups, which are mutually orthogonal. An optimal detection scheme can be used for detection of signals, among the members of the same group. As the number of users in each group is small optimal detection is not computationally difficult. At the same time inter group MAI is totally eliminated by virtue of their mutual orthogonality. By using this scheme the capacity of the system, using orthogonal codes can be increased by many folds, at the cost of some increase in complexity.

System Model

We are using an AWGN channel consisting of K users attached to a mobile station in a mobile cell. The received signals,

$$r(t) = \sum_{k=1}^{K} b_k s_k(t) + n(t) \tag{9.7}$$

where $b_k \in [-1,1]$, is the k*th* user's symbol, $s_k(t)$ is the orthogonal signature waveform of the k*th* user and $n(t)$ is AWGN. The signature sequences are taken from an Hadamard code-set. In a typical down link channel, the different orthogonal codes can be assigned to different users. In order to detect the signal of a particular user, the received signal $r(t)$ is correlated with the code of the user and output is sent to a threshold device to decide whether the binary symbol is 1 or -1. In this case the error performance is noise limited. As all the codes are mutually orthogonal there is no risk of MAI.

Orthogonal partitioning

Even though the orthogonal codes are interference free as mentioned earlier, the number of users is limited. Here we have come up with a method to double the number of users for a system using orthogonal codes, by adopting orthogonal partitioning and optimal detection scheme. The maximum number of users possible, in a mobile communication system using orthogonal codes is N, where N is the length of the code (processing gain). In order to double the number of users we form two sets of mutually orthogonal codes each consisting of $2^{N/2}$ codes spanned by N/2 basis codes catering to $2^{(N/2-1)}$ users. The users of each set can be detected by optimal multiuser detection method [7].

As an example, assume an orthogonal code of length 8 and in the un-partitioned case the number of users are limited to 8. In our method we are dividing the eight orthogonal codes, into two equal sets of length 8 each. Each set is used to form a four dimensional subspace consisting of eight codes. So each set consists of 16 antipodal codes spanned by 4 orthogonal codes catering to eight users. The codes belonging to one set is always orthogonal to codes belonging to the other set. Because of this, detection of users in one set is not affected by signals in other set (ie., there is no MAI between users of two sets but there is MAI between users of a particular set). To eliminate the intra-set MAI, the signals of each set can be detected by an optimal mutiuser detection scheme as explained below.

The Hadamard orthogonal codes are shown as columns in Table 9.1. Consider the codes in the last four columns. The eight codes spanned by these four codes are shown in Table 9.2. These eight codes can be used to carry the binary symbols of eight users of the first set. It is to be mentioned that these codes are not mutually orthogonal and hence they cannot be efficiently detected by simple correlation techniques or using matched filters. The data of the users in this set can be detected by optimal detection scheme.

Validation

The verification of the proposal was done by simulation using MATLAB. Here we have four users using four codes taken from Table 9.2. We form a look-up table corresponding to all possible 16 combinations of the user symbols and the four codes and this will be stored. When a particular combination is received, it will be correlated with all 16 combinations in the look-up table and the one giving maximum correlation (minimum Euclidian distance) will be selected. It is verified that the probability of error is solely decided by noise and MAI is eliminated. The MATLAB program is based on an algorithm in [29].

Conclusion

The above method can be extended to any number of users, which are integer powers of two. For example instead of having 16 users by using an orthogonal code of length 16, we can have 32 users having codes in four mutually orthogonal groups, each group having 8 codes. The computational complexity can be further reduced, by using Viterbi algorithm.

Table.9.1 Hadamard codes

-1	-1	-1	-1	-1	-1	-1	-1
-1	1	-1	1	-1	1	-1	1
-1	-1	1	1	-1	-1	1	1
-1	1	1	-1	-1	1	1	-1
-1	-1	-1	-1	1	1	1	1
-1	1	-1	1	1	-1	1	-1
-1	-1	1	1	1	1	-1	-1
-1	1	1	-1	1	-1	-1	1

Table. 9.2 Subspace spanned by the right four columns of

Hadamard codes in Table 9.1

-1	-1	-1	-1	-1	-1	-1	-1
-1	-1	1	1	-1	1	-1	1
-1	1	-1	1	-1	-1	1	1
-1	1	-1	1	-1	1	1	-1
1	1	1	1	1	1	1	1
1	1	-1	-1	1	-1	1	-1
1	-1	1	-1	1	1	-1	-1
-1	1	1	-1	1	-1	-1	1

9.5 A SIMPLE METHOD FOR CHANNEL ESTIMATION

A simple method is presented for channel estimation in CDMA system assuming noise-free channel. The detector vector corresponding to the first path, $\mathbf{d}_{11}$ is obtained using the MOE method and LMS algorithm. In this case it can be seen that $\mathbf{d}_{11}$ is orthogonal to the effective signature codes of every users including the first user. ie., $\mathbf{d}_{11}$ is orthogonal to all $\{\widetilde{\mathbf{s}}_k\}_{k=1}^{K}$. So we can write, $\mathbf{d}_{11}^T\widetilde{\mathbf{s}}_k = 0, \text{for all } k = 1 \text{ to } K$

$$\text{ie., } \mathbf{d}_{11}^T\widetilde{\mathbf{s}}_1 = \mathbf{d}_{11}^T[\mathbf{s}_{11} \quad \mathbf{s}_{12}]\mathbf{h}_1 = 0 \tag{9.8}$$

Similarly by considering the second path of the first user, we can write,

$$\mathbf{d}_{12}^T\widetilde{\mathbf{s}}_1 = \mathbf{d}_{12}^T[\mathbf{s}_{11} \quad \mathbf{s}_{12}]\mathbf{h}_1 = 0 \tag{9.9}$$

As we have already calculated $\mathbf{d}_{11}$ and $\mathbf{d}_{12}$ adaptively, and $\mathbf{s}_{11}$ and $\mathbf{s}_{12}$ are known, we can compute the channel matrix of the first user,

$$\mathbf{h}_1 = \begin{bmatrix} h_{11} \\ h_{12} \end{bmatrix} \tag{9.10}$$

as a solution to one of two equations above, subject to the constraint $h_{11}^2+h_{12}^2=1$.The phase ambiguity in the estimation, can be sorted out by adopting differential encoding and decoding. If the channel order is L, then there will be L equations in L unknowns and this can be solved in a manner similar to above. It can be seen that the above method is free from MAI and MPI. The simulation results for 3 users with number of paths 2, for the first user is shown in Table 9.3.

Simulation results

Table No. 9.3 Results of simple method for channel estimation. No. of users 3 No. of paths for the first user, 2

Trial No.	Actual channel parameters ($\mathbf{h}_1^T$)	Estimated channel parameters ($\hat{\mathbf{h}}_1^T$)
1	[.5 -.866]	[-.5001 .866]
2	[.5 .866]	[.5 .866]
3	[.3 .954]	[.3 .954]
4	[.6 .8]	[.6014 .799]

In this chapter we introduced some minor works done in wireless communication area some of which are directly connected with the main topic. In the next chapter we conclude the discussion.

Chapter 10

CONCLUSION

In this work a blind, adaptive multiuser detector with combined channel estimation is developed, analysed and performance validated. Computational complexity for the formation of the detector is found to be very low compared with competing methods. The bit error performance of the proposed detector in non-fading channel is found to match the ideal MMSE detector and in fading channel improved performance is observed. As a supplementary work a novel method for channel estimation is developed deriving motivation from the main work. Some minor works are also reported.

As a preliminary work, different multiuser detectors appearing in the recent literature were simulated and performance analysed. They include the non-adaptive, non-blind MMSE and decorrelating detectors. MMSE and decorrelating detectors, which use the knowledge of signature codes of all users, received signal amplitudes, symbol timing etc., were first formed for single path scenario. BER were plotted against SNR.

The signature codes of all users and the received signal amplitudes are usually unavailable in a practical scenario. Adaptive methods have been tried to overcome these eventualities. A data-aided MMSE detector was implemented using stochastic gradient methods using LMS algorithm. A blind detector was implemented in batch mode using the DMI method. A constrained minimum output energy (CMOE) detector was implemented using the RLS algorithm. A CMOE detector was also implemented using the LMS algorithm. The performance of the minimum variance receiver by Tsatsanis was compared with an ideal MMSE receiver. It was seen that at small SNR the performance of the Tsatsanis' receiver is inferior to an ideal MMSE receiver. As SNR improves the performance difference between the two detectors gradually vanishes.

Another blind technique for detector implementation is subspace method. Both decorrelating detectors and MMSE detectors were implemented blindly in a non-adaptive manner. It was found that the performance of the subspace-based MMSE detector was inferior to that of the ideal MMSE detector because in the former subspace parameters are derived from the noisy received signal. An adaptive version also was implemented using the subspace tracking principle. This adaptive method was found to be superior to the RLS version of the MOE method, in terms of computational complexity. It was verified that compared to ideal MMSE detector the performance of the subspace method is highly unreliable.

In the proposed work a multiuser detector with integrated channel estimation is considered. Here the decorrelating or MMSE detectors corresponding to each path of UOI is first determined in a blind, adaptive manner using MOE criterion and LMS algorithm. The received signal is then projected onto the subspace spanned by these filter vectors to obtain the final detector. The performance of the receiver is on par with that of the non-adaptive, non-blind ideal MMSE detector. The attraction of our method is that the channel is not explicitly estimated and the computational complexity is lower when compared with adaptive detection technique using subspace or RLS method. Another noteworthy feature of our method is that detection can be carried out even when the auto-correlation matrix, of the received signals are rank deficient. The RLS method fails to operate in such a scenario. The proposed receiver is neither dependent on estimated channel parameters nor on training sequences and hence differential encoding and decoding is adopted here.

The performance of the proposed detector was compared with subspace method and RLS version of the MOE method. It can be seen that the computational complexity of our method is only O(N) per iteration for single path case and that of the subspace method is O(NK), while RLS method has a computational complexity of $O(N^2)$. From the performance evaluation of the single path case, it can be seen that our method far excels the RLS method and subspace method. In a multipath case, subspace method needs channel estimate to perform data detection while our method performs data detection and channel estimation in an integrated fashion. In multipath case we have also compared the Buzzi's method with the proposed method. It can be seen that the computational complexity of Buzzi's method is higher than that of our method. Moreover, the performance of Buzzi's method measured in terms of correlation coefficient is poor, compared to unity of our method.

The mobile channels are characterised by a fading frequency selective channel. Our detector was tested in a mobile scenario too, and the performance was found to be very encouraging. Constant amplitude, varying phase channel is first simulated. Number of users participating in the simulation is four and the desired user has two paths. The channel parameters of the desired user, is generated by passing noise sequences through two identical second order, low-pass Butterworth filters. The norm of the generated channel parameters is maintained at unity by normalization. The principal eigen vector of the time-varying auto-correlation matrix of the projected signal is up-dated using the rank-one PASTd algorithm. The performance of the obtained detector was compared with an ideal MMSE detector operating under identical conditions but in a non-fading channel. The performance difference in this case was found to be small. The performance of the proposed detector was also compared with a non-adaptive MMSE detector used in the fading channel. It was verified that non-adaptive MMSE detector fails miserably in a fading channel.

The performance of the detector was also tested in a Rayleigh fading channel. The two-path channel of the desired user is Rayleigh distributed. Here also channel parameters of the desired user, is generated by passing noise sequences through two identical second order, low-pass Butterworth filters, but no normalization is done here. In this case also, it was verified that the performance of the proposed detector is close to the ideal MMSE detector used in an identical channel but without fading at low SNR. But as SNR increased the performance difference between the proposed detector and the ideal MMSE detector increases.

A blind, unbiased, adaptive method for channel estimation in multipath CDMA channels is also presented. Usually the estimated channel parameters are biased due to the presence of MAI, MPI and noise. In this method the filter vectors corresponding to different paths are obtained. The obtained filter vectors are then orthogonalized as has been explained. The received signal is then projected onto this orthogonolized vectors and subsequent averaging over a reasonable number of symbols will give the unbiased channel estimate. Various miscellaneous works were also undertaken besides the main work mentioned hitherto. An adaptive decorrelator is implemented which is not possible using conventional methods. A simple fading-free decorrelator also was implemented in a noiseless scenario. In this case the decorrelator was independent of channel gains of the interfering users and changes in the channel gains of the desired user only affects the optimum performance but data detection goes on uninterrupted. The conventional MOE detector is very sensitive to signature code mismatch and channel distortions and does not perform satisfactorily in the presence of multipath propagation. The detector, which we proposed, can be used as a robust detector in such a multipath scenario. A novel scheme for enhancing the capacity of a mobile communication system, which conventionally uses orthogonal codes, was also experimented. A simple method for channel estimation also was introduced towards the end.

Future scope

The proposed method can be extended to an asynchronous system and to systems which does not assume the timing offset of the desired user (ie a timing-free multiuser detector suitable for dispersive channels with reduced computational complexity can be thought). The method can also be extended to multiple input multiple output (MIMO) space-time coded systems where in transmitters and receivers are fitted with multiple antennas or antenna arrays.

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