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Multiple-Access Interference Rejecting Receivers in DS-CDMA Communication System

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Abstract

The growth of Personal Communications, the keyword of the 90s, has already the signs of a technological revolution. The foundations of this revolution are currently set through the standardisation of the Universal Mobile Telecommunication System (UMTS), a communication system with synergistic terrestrial and satellite segments. The main characteristic of the UMTS radio interface, is the provision of Integrated Services Digital Network (ISDN) services. Services with higher than voice data rates require more spectrum, thus techniques that utilise spectrum as efficiently as possible are currently at the forefront of the research community interests. Two of the most spectrally efficient multiple-access technologies, namely, Code Division Multiple Access (CDMA) and Time Division Multiple Access (TDMA) concentrate the efforts of the European telecommunity.

This thesis addresses problems and proposes solutions for CDMA Spread Spectrum (SS) systems. A limitation to the capacity of conventional DS-CDMA systems is multiple-access interference (MAI) produced by co-channel users. The design of MAI rejecting receivers with 'Near-Far' resistance is a good technique for combating the effect of co-channel interference in multiple-access channels. The 'Near-Far' resistant characteristic of these detectors reduces considerably the requirements of the power control loops currently found in commercial CDMA systems.

The strategy for the downlink mobile channel, where the receiver is the mobile handset, is to employ a single-user receiver with multi-user interference cancellation to detect the desired user's signal. Two adaptive single-user handset receivers are proposed in this thesis and their performance obtained by computer simulation. The first detector is an adaptive Minimum Mean Square Error (MMSE) receiver architecture with the capability of combating the 'Near-Far' problem and rejecting the multi-user interference. This adaptive structure allows the receiver to counter interference and noise. MMSE detection schemes offer significant advantages compared with conventional correlation based receivers, as they are 'Near-Far' resistant over a wide range of interfering power levels. MMSE detectors are also found to have significant performance gains over other well established interference cancellation techniques like the decorrelating detector, especially in heavily loaded system conditions. The new modified adaptive MMSE receiver proposed here and it has been used to function in a multipath-fading channel with Doppler, typical of a mobile channel. The second detector is a new adaptive Multi-Layer Perceptron (MLP) neural network receiver. This architecture has the capability to combat the 'Near-Far' problem and reject the multi-user interference. The non-linear processing units in the structure of the artificial neural network allow the receiver to draw subtle boundaries between the wanted signal and unwanted signals in the multiple-access DS-CDMA environment and hence it has a good 'Near-Far' resistance over a wide range of interfering power levels.

For the uplink DS-CDMA channel, where the receiver is located in a base-station in the centre of the cell, the strategy is to use a multi-user receiver to detect all co-channel users' signals in the cell simultaneously. The optimum maximum-likelihood multi-user detector is currently too complex to be implemented in commercial systems. The recurrent neural network receiver as a multi-user receiver is extremely suitable for combating the effect of co-channel interference in the DS-CDMA environment and its ability is found in this work identical to the maximum-likelihood receiver. In addition, the implementation complexity of the recurrent neural network receiver, especially for large number of users, is considerably lower than the implementation complexity of the maximum-likelihood receiver.

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Publications

The author has published the following papers associated with the work presented in this thesis:

1 H. Khoshbin-Ghomash and R. F. Ormondroyd, " An Adaptive DS-CDMA Receiver for Multipath and Multi-User Environments," *Proceedings IEEE International Conference on Universal Personal Communications (ICPUC)*, Vol. 1-2, Ch. 216, pp. 1183-1187, Florence, Italy, Oct. 1998.

2 H. Khoshbin-Ghomash and R. F. Ormondroyd, " An Adaptive Neural Network Receiver for CDMA Multi-User Interference Cancellation in Multipath Environments," *Proceedings IEEE Military Communications Conference (MILCOM)*, Vol. 3, Ch. 202, pp. 767-771, Boston, Massachusetts, USA, Oct. 1998.

3 H. Khoshbin-Ghomash and R. F. Ormondroyd, " Neural Network Multi-User Receiver for Direct-Sequence Code-Division Multiple-Access (DS-CDMA) Multimedia Systems," *Proceedings 4th Annual International CSI (Computer Society of Iran) Computer Conference (CSICC)*, Vol.1, pp. 199-203, Teheran, Iran, Jan. 1999.

4 H. Khoshbin-Ghomash, R. F. Ormondroyd and R. W. Dunn, " Low Complexity Neural Network Structure for Implementing the Optimum Maximum-Likelihood Multi-User receiver in a DS-CDMA Communication System," *Proceedings IEEE 50th Vehicular Technology Conference (VTC)*, Vol. 2, pp. 643-647, Amsterdam, Netherlands, Sep. 1999.

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List of Symbols

$(.)^*$	Complex conjugation
$(.)^T$	Transposition
$(.)^H$	Hermitian transposition
$A_k(t)$	Amplitude of the kth user
$b_k(t)$	Data bit of the kth user
$\beta(n, i)$	Forgetting factor
$c_k(t)$	Signature waveform of the kth user
$C(.)$	Correlation metrics
$d(n)$	Desired value in the nth iteration
$e(n)$	Error value in the nth iteration
E	Energy function
E_i	Energy per bit of the ith user
E_b/N_0	Bit energy to noise power spectral density ratio
$exp(.)$	Exponential function
f_c	Chip rate
f_b	Bit rate
f_D	Doppler frequency
$h(\tau; t)$	Channel impulse response
$h_{i,k}$	Cross-correlation of the ith and the kth signature waveforms
H	Correlation matrix
K	Total system users
L	Number of data bits in a data block
λ	Eigenvalue of the correlation matrix
N	Length of the signature sequence in chips
$n(t)$	Noise signal
P	Cross-correlation vector
P_{BER}	Probability of error
$Q(.)$	Gaussian integral function
$r(t)$	Received Signal
R	Auto-correlation matrix
$s(t)$	Transmitted signal
t	Time
$tanh(.)$	Tangent hyperbolic function

T_b	Bit period
T_c	Chip period
τ_k	Random delay
μ	Step-size parameter
W	Weight Vector
ω_0	Carrier frequency
z_k	Noise term
$\Lambda(\mathbf{b})$	Log-likelihood function
$\delta(.)$	Impulse function
σ^2	Variance of noise
$\varphi(.)$	Activation function
θ	Threshold value

List of Abbreviations

AWGN	Additive White Gaussian Noise
BER	Bit Error Rate
BPSK	Binary Phase Shift Keying
CDMA	Code Division Multiple-Access
DPSK	Differential Phase Shift Keying
DS	Direct Sequence
DS-CDMA	Direct Sequence Code Division Multiple-Access
EGC	Equal Gain Combination
FDMA	Frequency Division Multiple-Access
FH	Frequency Hopping
FIR	Finite Impulse Response
GSM	Global System for Mobile Communication
ISDN	Integrated Services Digital Network
LMS	Least Mean Square
LS	Least Square
MAI	Multiple-Access Interference
ML	Maximum Length
MLP	Multi Layer Perceptron
MMSE	Minimum Mean Square Error
MRC	Maximum Ratio Combination
NN	Neural Network
PG	Processing Gain
PS	Pseudorandom Spreading
RLS	Recursive Least Square
RNN	Recurrent Neural Network
SNR	Signal to Noise Ratio
SS	Spread Spectrum
SSE	Sum-Square Error
TDMA	Time Division Multiple-Access
TH	Time Hopping
UMTS	Universal Mobile Telecommunications System

Chapter One

Introduction

1.1 Introduction

The invention of the telephone in the 19th century was the first step towards removing the barriers of space and time for communication between people. The second step was the successful deployment of radio communication, which was the starting point for development in the wireless communication. In the future, wireless personal communications will be as common as the wireline telephone is today. It can now provide reliable communication and combines voice, data, fax and image into a single portable handset. In this situation, the increased number of users and the growing demand for personal communication networks will require a new generation of mobile system such as the Universal Mobile Telecommunication System (UMTS) [1- 1]. This is the European vision for the next generation of mobile radio systems, where analogue mobile phone systems were taken to be the first generation and the existing digital systems are the second generation.

The first generation of the cellular radio communication was based on the Frequency-Division Multiple-Access (FDMA) systems that used analogue frequency modulation scheme to facilitate simultaneous communication between users. The major disadvantage of analogue cellular system was the capacity limitations [1- 2]. In order to solve the capacity problem, a transition in operational schemes was made from analogue FDMA systems to digital cellular FDMA and Time-Division Multiple-Access (TDMA) as the second generation of the cellular systems.

The application of digital FDMA and TDMA schemes to the cellular mobile radio has led to an increase in user capacity by a factor of about 3 to 4 [1- 3] over what was provided by their analogue counterparts. The Pan-European Global System for Mobile Communication (GSM) is typical of second generation systems that allows the user to use its handset in most countries in Europe to communicate voice, fax and data [1- 1]. The number of GSM subscribers recently passed 100 million, and it is predicted that by 2005 there will be more than a billion mobile phone subscribers around the world. In this case, to increase the quality and overcome the problem of capacity, the development of new standards is necessary. The objectives of the next generation system can be summarised as mass-market capability, world-wide services, low cost, better quality and ability to provide different services e.g. e-mail, web access and video.

One of the most important new standards is the UMTS [1- 4]. It is a communication concept which will try to integrate different services into a common standard. It is expected that UMTS will provide following services [1- 5]:

◆   Existing mobile and fixed telecommunications services at data rates of up to 2 Mbits/sec.

◆   Pan-European mobile navigation, vehicle location and traffic information services.

◆   Global portability for the handsets.

◆   A single system for residential, office, cellular and satellite environments.

◆   Support for video and high data rate services in a range of UMTS ranging from pocket handset to terminals.

◆   Users will be able to buy bandwidth as well as time, with low rate voice communication being the cheapest and video and data services being the most expensive.

To bring this vision to fruition, major improvements in the current state of wireless technology are necessary.

1.2 Multiple-Access Techniques

In general, there are several different ways in which multiple users can send information through the communication channel to the receiver. Frequency-Division Multiple-Access (FDMA), Time-Division Multiple-Access (TDMA) and Code-Division Multiple-Access (CDMA) are three famous multiple-access techniques.

In FDMA, the available bandwidth in the transmission channel is subdivided into N frequency non-overlapping sub-channels as showing in Figure 1. 1. In this way, each user can transmit information via one of the assigned frequency domain sub-channels. To avoid cross-talk between adjacent users, suitable size guard bands are usually provided between sub-channels.

Another method of creating multiple sub-channels for multiple-access transmission, is TDMA. In this method the frame duration, T_f, is subdivided into N non-overlapping sub-intervals each with duration T_f/N. In TDMA, each user transmits information within a particular time slot in each frame. In this method, accurate synchronisation for all users is needed and to avoid cross-talk between adjacent users, suitable guard intervals are usually provided between time slots.
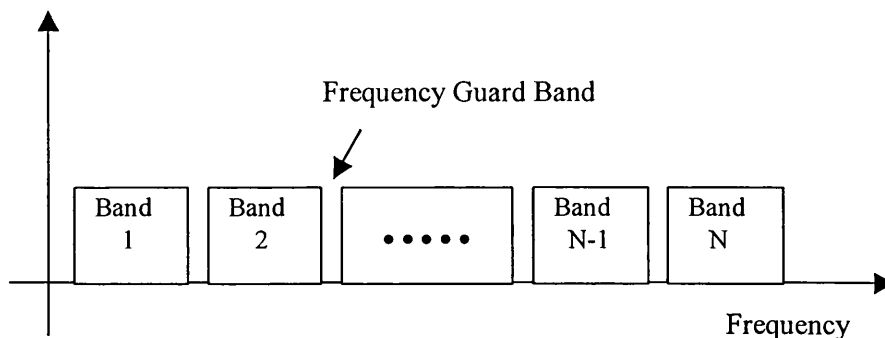
Figure 1. 1: Subdivision of the transmission channel into non-overlapping bands in FDMA.

An alternative method to either TDMA or FDMA is to allow more than one user to share a channel or sub-channel by using a code or signature [1- 6]. This multiple-access method is called CDMA. In this method, each user is assigned a unique signature waveform to transmit its information into the multiple-access channel. In the CDMA base-station receiver, the transmitted data from the wanted user can be separated and recovered by taking the cross-correlation of the received signal with each of the possible user's signature waveform. If the assigned signature waveforms have a small cross-correlation to each other, the cross-talk at the output of the receiver will be low. In this case, the information of the desired user can be separated from the information of the other co-channel users by using a correlator or an equivalent operation based on a digital matched filter. Figure 1. 2 shows the time-bandwidth utilisation of the three multiple-access techniques described above.
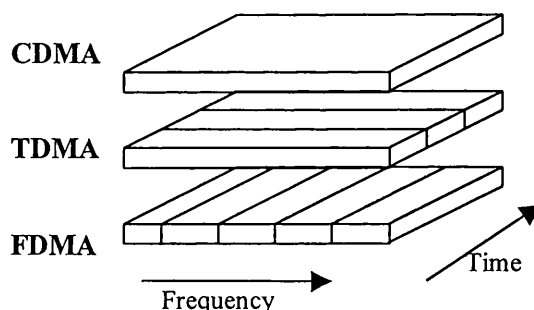
Figure 1. 2: Time-bandwidth utilising of three multiple-access techniques.

In CDMA, multiple users can utilise the same available bandwidth by using different orthogonal spreading signature sequences and in this situation the interference between users is minimised because of the orthogonality of the spreading sequences.

The development of the CDMA scheme for digital cellular radio and other wireless systems has primarily been for the reason of achieving higher user capacity [1- 2]. Because the CDMA has a capacity that is only interference limited, unlike TDMA and FDMA capacities which are bandwidth limited, any reduction in interference translates directly into a proportional increase in capacity. Therefore by using interference suppression techniques, the capacity of the CDMA is increased in comparison with other multiple-access schemes. This advantage of CDMA over TDMA and FDMA becomes even greater in digital cellular systems where the CDMA can use the advantage of frequency re-use for all cells and this causes the capacity increasing by a large percentage of the normal frequency re-use factor. It is shown that the net capacity improvement of CDMA over TDMA and FDMA schemes is on the order of 4 to 6 [1- 2], [1- 3].

The maximum number of users that can be accommodated in multiple-access CDMA channel is determined by the degree of bit error rate (BER) performance degradation that is caused with the co-channel interference. In both TDMA and FDMA, the level of BER performance remains approximately constant with increasing the number of users, in other words; they have a hard limit capacity on the maximum number of users whereas CDMA has soft limited capacity, assuming sufficient orthogonal codes are available.

The European Telecommunications Standards Institute on UMTS has selected CDMA among the potential contending multiple-access techniques for the third generation of cellular mobile communication systems across Europe [1- 7][1]. The principal aim is to provide users of wireless terminals access to the projected Broadband Integrated Services Digital Network (BISDN).

The advantages of CDMA over other multiple-access schemes can be listed as below [1- 8]:

♦ Universal frequency re-use (frequency allocation problem eased).
♦ The lower power requirement of CDMA (by using the advantage of processing gain) can improve the handset talk times.
♦ Using multipath signals for diversity reception (with RAKE receiver).

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[1] It was suggested that a combination of wide-band CDMA and time-duplex CDMA being used for paired spectrum and unpaired bands respectively. Because there is more paired than unpaired spectrum, wide CDMA will be the dominant within in UMTS [1- 1].

◆ A large number of users can be accommodated in a given bandwidth in compared with FDMA and TDMA.

◆ In CDMA, it is not needed to use time or frequency guard bands and hence bandwidth will be used more efficiently than with other types.

◆ In CDMA, channel usage need not to be monitored.

There are several problems in using the CDMA scheme for multiple-access mobile radio communication that can be highlighted as below:

◆ Higher complexity for spreading and despreading process.

◆ Irreducible error rate due to effect of other co-channel users.

◆ Finite processing gain because of using limited length of spreading sequences.

◆ Need for orthogonal signature sequences.

◆ Optimum capacity needs tight power control to combat the 'Near-Far' effect.

◆ Multipath-fading channel causes loss of orthogonality between codes.

In order to obtain higher quality and bit rate in the next generation of mobile radio, it is needed to overcome the channel limitations by employing some techniques. These techniques can be summarised as effective channel estimation and equalisation, effective air interface, effective modulation, effective interference cancellation and effective channel coding.

As it is not possible to make the pseudorandom spreading waveforms of each user completely orthogonal in a mobile multipath channel, there is a degree of interference between co-channel users. In this case the desired user's signal is subject to interference from the other users signals, which may be received at a higher power level than the wanted signal. Power control techniques are traditionally used to solve the 'Near-Far' problem in CDMA. In these techniques, the output power of each mobile is adjusted to ensure that all signals arrive at the same energy level at the base-station receiver. It is clear that using the power control techniques increases the implementation complexity and wastes the system bandwidth. A better strategy is to employ a receiver, which has 'Near-Far' resistance and has the ability to remove the multiple-access interference (MAI).

The fundamental limitation of CDMA is the 'Near-Far' effect. It makes the system unusable in the mobile environment as the number of users increases. The first references in interference cancellation, due to the increasing interest in CDMA for commercial applications, are those of Schneider [1- 9] in 1979 and Kohno [1- 10] in 1983. In the recent years a significant number of

papers have been devoted to the analysis and design of the 'Near-Far' resistant receivers for CDMA. They include: the optimum maximum-likelihood [1- 11], successive interference cancellation [1- 12] and the decorrelating receiver [1- 13]. Lupas and Verdu [1- 13], [1- 14] have provided a theoretical treatment of 'Near-Far' resistance, Varanasi *et al* [1- 12], [1- 15] and Duel-Hallen [1- 16], [1- 17] have investigated various optimal and sub-optimal multi-user receivers.

These receivers show good 'Near-far' resistance in a CDMA environment but they generally need accurate additional information concerning the channel characteristic and they can have high implementation complexity to achieve the desired level of interference cancellation. These requirements significantly increase the implementation difficulties of practical receivers in real situations particularly when optimum solutions are required. Therefore, another important way in research in multi-user detection is the design of adaptive detectors that self-tune the detector parameters from the observation of the received signal [1- 18].

The adaptive minimum mean square error (MMSE) and multi-layer perceptron (MLP) neural network receivers which are proposed in this work, in general, have lower implementation complexity than current proposed systems and in same cases do not need apriori information to achieve the desired performance. These receivers attempt to remove MAI from the received signal with the aid of known training sequences inserted into the transmitted data.

Due to the simple structure and good characteristics, the adaptive MMSE receiver attracts much attention to be implemented in future cellular and personal communication systems. Many researchers investigated the performance of the adaptive MMSE receiver. Madhow and Hoing [1- 19], Rapajic and Vucetic [1- 20], Miller [1- 21], [1- 22], [1- 23], Pateros and Saulnier [1- 24], Yoshida and *et al* [1- 25] proposed this receiver for use in the CDMA systems.

The first paper that considered the application of adaptive neural network receivers to multi-user detection in CDMA environment is due to Aazhang, Paris and Orsak [1- 26]. They studied a multi-layer perceptron structure as a receiver in CDMA environment. This task has been continued by other researcher such as Mitra and Poor [1- 27], [1- 28], Chen, Mulgrew and McLaughlin [1- 29], Miyajima, Hasegawa and Haneishi [1- 30], Hottinen [1- 31] in the recent years.

1.3 Thesis Outline

The work presented in this thesis, which has been started from 1996 when the UMTS had not been defined as a system, focuses its attention on MAI rejecting receivers in CDMA mobile radio environment. In this way the theory, design, and performance of adaptive receivers for the downlink channel of a CDMA system are studied. Also the potential of neural network structures for use as single-user receivers in the downlink CDMA channel and as a multi-user receiver in the uplink CDMA channel are considered. These receivers are good alternatives to currently proposed MAI rejecting receivers that reduce the need for accurate power control techniques. The proposed structures have a number of attractive features compared with the current techniques to combat the effect of 'Near-Far' in CDMA communication systems.

Chapter two provides an introduction to Direct Sequence CDMA (DS-CDMA) communication systems. It contains a brief survey of different techniques to implement receivers in the DS-CDMA communication environment. A description of operating schemes, the capacity, BER performance, and the 'Near-Far' effect are given along with an illustration of the multiple-access channel's model in DS-CDMA. The theory and implementation of the conventional matched filter receiver and the maximum-likelihood receiver are considered and their performances are evaluated. The sub-optimal DS-CDMA receivers are introduced and their theory and implementation are investigated.

Chapter three considers the adaptive MMSE receiver in DS-CDMA environment. It investigates the abilities of adaptive MMSE receiver for despreading the DS-CDMA signals, combating the effect of interference and using the multipath phenomena of channels for diversity reception in DS-CDMA system. A description of adaptive algorithms, the theoretical treatment of the adaptive MMSE receiver, and a novel modification of the structure of MMSE receiver to function in a dynamic multipath-fading environment are given.

Chapter four focuses its attention into the artificial neural network techniques for receiving the signal in DS-CDMA environment. Benefits of the neural network, models of neurons, various structures of neural networks, and learning algorithms are given. Also a new adaptive MLP neural network receiver is introduced that has the capability of combating the 'Near-Far' problem and rejecting the multi-user interference in a multipath DS-CDMA channel. The application of the artificial neural network structures as single-user and multi-user receivers in different channel model scenarios of DS-CDMA system are also considered in this chapter.

Chapter five discusses appropriate computer simulation techniques for DS-CDMA mobile system, which are used to generate the results presented within this thesis.

Chapter six presents simulation results for receivers in the downlink and uplink DS-CDMA mobile environments. The focus for the downlink channel is the adaptive MMSE and adaptive MLP neural networks as single-user receivers. A comparison is drawn with the performance of the conventional matched filter receiver and the RAKE receiver for different channel model scenarios. For the uplink channel, the performance of the recurrent neural network receiver where used as a multi-user receiver in multiple-access DS-CDMA channel is evaluated through a comparison with the performance of the conventional, the decorrelating and the optimum maximum-likelihood receivers.

Conclusion and recommendations for future work are given in chapter seven.

Appendix A considers the pseudorandom sequences as signature waveforms for DS-CDMA systems. In this appendix the performance of ML and Gold codes employed in this work, are evaluated.

Appendix B illustrates models of the multipath channel in mobile communication. This Appendix considers the impulse response of multipath channel in different environments, frequency selective Rayleigh fading channels and different techniques for estimating the delay profile and attenuation coefficients of multipath channel.

Appendix C contains some results from independents published papers that are employed to validate the simulation software that has been used to produce the results in this thesis.

Appendix D contains a copy of recent publications by the author, which have been published associated with the work presented in this thesis. In the first paper, a novel modification for the adaptive MMSE receiver is introduced to combat the effect of multipath fading in the downlink mobile channel. In the second paper, a new adaptive MLP neural network receiver is introduced that has the capability of combating the 'Near-Far' problem and rejecting the multi-user interference in a multipath channel. In the third and the fourth papers, an artificial neural network approach to multi-user detection for the uplink mobile channel is considered. It is shown that the performance of this receiver is the same as the maximum-likelihood multi-user receiver but its implementation complexity, especially for a large number of users, is lower than the implementation complexity of the maximum-likelihood receiver.

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Chapter Two

DS-CDMA Communication System

2.1 Introduction

Spread Spectrum (SS) wireless systems use a transmission bandwidth which is greater than the minimum required for sending the information. There are some benefits in increasing the transmission bandwidth and one of the most important of them is the resistance to interference. The increasing of transmission bandwidth is achieved with a pseudorandom spreading (PS) waveform, which is called the signature waveform. This signature waveform is independent of the data. By using the same signature waveform at the receiver for despreading, the desired user's signal will be extracted from all other signals that use the same channel simultaneously. There are three basic spread spectrum methods, Direct-Sequence (DS), Frequency-Hopping (FH), Time-Hopping (TH), as well as several Hybrid Methods. Although both direct-sequence and frequency-hopping methods have attractive features to be candidate modulation schemes for new generation of mobile communications, but at the present time the direct-sequence code-division multiple-access (DS-CDMA) has the highest attention to be implemented for this reason.

Multiple-access interference (MAI) is a factor that limits the capacity and the performance of DS-CDMA communication systems. MAI refers to the interference between direct-sequence signature waveforms of different users that share a common channel. This interference is the result of the random time offsets between signals, which make it impossible to design the signature waveform signals to be completely orthogonal[1] in real mobile channel. However the MAI caused by any one user is generally small, but when the number of interfering signals or their power increase, MAI become substantial.

The conventional matched filter receiver, which is the simplest receiver used in a DS-CDMA system, does not take into account the existence of MAI. It follows a single-user detection strategy in which each user's data is detected separately without regard to the other co-channel users' signals. Because of interference between users' signals, a better strategy is to use some kind of receiver that deletes or reduces the effect of other user signals on the desired user signal [2- 1]. In these receivers, the information of other users is used to improve the performance of the receiver to reject the interfering signals. These receivers are called multi-user receivers and have the potential to provide significant additional benefits for DS-CDMA systems [2- 2].

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[1] Two signature waveforms are called orthogonal if their cross-correlation equals to zero.

The development of multi-user detection has proceeded along a path that is typical of other areas in communications. Initially, the optimum solution was obtained along with the best possible performance in the Additive White Gaussian Noise (AWGN) channel [2- 2]. That result showed that there is a huge gap between the performance of the optimum and the conventional single-user detector that neglects the presence of MAI. The conventional single-user detector is a simple receiver, which uses a correlator or matched filter to despread the received signal followed by a decision device to detect the transmitted bits. Also it has been shown that the optimum multi-user detector is not sensitive to the 'Near-Far'[2] effect. This feature of multi-user detection avoids the need for accurate power control in the mobile communication systems, which increases the complexity of receivers. In other words, an increase in complexity in the base-station receiver enables a considerable reduction in the complexity of the mobile handsets. The major disadvantage of the optimum multi-user receiver is its implementation complexity, which increases exponentially with increasing number of co-channel users. However the best performance in the optimum receiver is achieved by using the all other available information such as the signature waveform, timing, amplitude and phase of all co-channel users' signals, which is not normally used in many calculations.

The second stage in the development of the multi-user detection technologies was to analyse and design sub-optimal detectors that could achieve significant performance gains over the conventional detectors without increasing the complexity exponentially with increasing numbers of users. In this way, the decorrelating detector was introduced and investigated by Lupas and Verdu [2- 3], [2- 4]; the multistage detector by Varanasi and Aazhang [2- 5], [2- 6]; the decision feedback multi-user detector by Duel-Hallen [2- 7], [2- 8]; and some sub-optimum detectors by Xie, Rushforth and Short [2- 9], [2- 10].

In order to the mobile environments, the design of multi-user detectors optimised for use in channels that include fading, multipath or noncoherent modulation has attracted considerable attention. Examples of this are the works of Varanasi [2- 11]; Vasudevan and Varanasi [2- 12], [2- 13]; Zvonar and Brady [2- 14], [2- 15], [2- 16]; Fawer and Aazhang [2- 17].

The multi-user detectors described above depend on various parameters being known in advance such as the received signal's amplitude and the cross-correlations between signature waveforms. In practice, these are usually not fixed and known prior to call set-up. Therefore, another important research direction in the multi-user detection has been the design of adaptive

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[2] This effect will be explained in the next section.

detectors that self-tune the detector parameters from the observation of the received signal [2-18].

This chapter contains a brief survey of different techniques that can be used for implementing receivers in the DS-CDMA communication environment. First of all, a description of a DS-CDMA system is presented in the following section and it will be followed by a description of the multiple-access channel model. The conventional technique of detecting the DS-CDMA signals is the subject of the fourth section and the fifth section considers the maximum-likelihood multi-user detection. The study of sub-optimal detectors is the subject of the sixth section and in the final part, the use of neural network structures as DS-CDMA receivers are considered

2.2 DS-CDMA System Description

In a DS-CDMA communication system, each user transmits a data sequence of rectangular pulses from the set of ±1 with a period of T_b. In this case, each user is assigned an independent signature waveform of chip period T_c, which is used to modulate the data bits in the data sequence. This converts the data signal to a wide-band spread spectrum signal and it is ready to be modulated by a carrier signal.

The selection of signature waveforms depends on a number of factors including system capacity, data rate and bandwidth as well as the properties of the chosen signature waveform set such as the auto-correlation and cross-correlation between set members[3].

2.2.1 Operating Schemes of the DS-CDMA System

A typical DS-CDMA system can operate one of two ways: either in a synchronous mode or an asynchronous mode. In a synchronous transmission scheme, the relative delay for all users is set to zero. In this case, the signature waveform of all users is aligned in time to be nearly orthogonal in order to maximise the capacity of system. This transmission technique decreases the amount of co-channel interference but the complexity of the system is increased. Another alternative is to permit users to transmit their information at any time. In this case, the complexity of the system decreases but the amount of co-channel interference is increased. This

is because of changing the near orthogonality between signature waveforms by random time delays.

2.2.2 The Capacity of the DS-CDMA System

The capacity of the DS-CDMA system is interference limited, unlike FDMA and TDMA that are bandwidth limited. Hence, any reduction in the interference converts directly into a capacity increase and for this reason, the receivers with interference rejection ability are of current interest because of their potential for improving capacity.

In a multi-user DS-CDMA channel, which includes K users, the desired user with the received power P_d is subject to interference from $K-1$ other users, each with received power P_i. In this case, the signal to interference ratio can be expressed as below:

$$SIR = \frac{P_d}{\sum_{\substack{i=1 \\ i \neq d}}^{K} P_i} \qquad (2\text{-}1)$$

The bit energy to noise power spectral density ratio is a better parameter, which is independent of the modulation technique and its performance. This is derived from equation (2-1) by using the data bit rate R, the total system bandwidth W, and the noise power η.

$$E_b / N_0 = \frac{P_d W / R}{\sum_{\substack{i=1 \\ i \neq d}}^{K} P_i + \eta} \qquad (2\text{-}2)$$

By using the above equation, the value of K can be determined for a given E_b/N_0. The value of W/R is the processing gain of the DS- CDMA system, which equals to the number of chips in a signature waveform word. It is clear that the performance of the DS-CDMA system degrades gracefully when the number of interfering users increases. In this case, an additional user can always be accommodated with the price of some degradation in the performance of system. However in the FDMA and TDMA, a user is blocked until a frequency slot or time interval

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[3] It will be explained in Appendix A.

becomes available. This can be interpreted as hard limit capacity in the FDMA and TDMA but in the DS-CDMA, the capacity of system is softer.

2.2.3 Bit Error Rate Performance of the DS-CDMA System

Bit error rate is one of the most useful measures of the communication system performance. The detection of signals may be divided into two major categories, coherent detection and non-coherent or differential detection. In the former, the receiver requires knowledge of the carrier phase in order to detect the incoming signal. On the other hand, differential detection does not require the knowledge of the carrier phase instead it utilises the phase difference between two consecutive symbols. In order for differential detection to work, the data have to be encoded differentially.

In a phase shift keying (PSK) modulation scheme, the transmitted data is encoded by the phase of the sinusoidal waveform $s_i(t)$. The incoming data is first grouped into M/2 bits, which are then applied to the modulator every T seconds to set the phase of $s_i(t)$ according to a certain constellation. The general analytical expression for a PSK signal is:

$$s_i(t) = \sqrt{\frac{2E}{T}} \cdot \cos[\omega_o t + \phi_i(t)]$$

(2-3)

where

$$\phi_i(t) = \frac{2\pi i}{M}, i = 0,...,M-1$$

(2-4)

In equation (2-3), T is the duration of a symbol and E is the energy of signal per symbol and in equation (2-4), M is the number of different phases, which have been used to define the PSK signal.

Two of the simplest forms of the PSK signals are binary and differential PSK (BPSK and DPSK) in which $M = 2$. In this case, there are only two phases, usually zero and π, which are used to generate the PSK signal.

It is noted that the BPSK signal should be coherently detected whereas DBPSK signals can be both coherently and differentially detected. Due to the fact that differential detection relies on the phase difference between consecutive symbols, when an error occurs it can propagate and result in more than one symbol being incorrectly decoded. However, since differential detection does not require knowledge of the carrier phase, a much simpler receiver may be implemented. In addition, at high E_b/N_0, the DPSK modulation scheme performs almost as well the BPSK in the AWGN channel. The performance of the PSK is usually measured in terms of the probability of error, P_e, or bit error rate as a function of the signal to noise ratio per bit (E_b/N_0). For channels where the AWGN is the predominate interference and the level of co-channel interference is negligible, the probability of error for coherent BPSK is as below:

$$P_e = Q\left(\sqrt{\frac{2E_b}{N_0}}\right) \qquad (2\text{-}5)$$

where E_b is the energy per bit, N_0 is the noise power spectral density and $Q(x)$ is the Gaussian integral function that is defined as below:

$$Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^\infty e^{-t^2/2} dt \qquad (2\text{-}6)$$

With differentially coherent detection, the bit error rate is given by:

$$P_e = \frac{1}{2} \exp\left(\frac{-E_b}{N_0}\right) \qquad (2\text{-}7)$$

Equations (2-5) and (2-7) describe the bit error rate of the optimum single-user receiver and they represent the limit of performance when the MAI can be completely cancelled from the received signal in a multi-user environment. These equations also represent the lower bound on the achievable performance of a 'Near-Far' resistance receiver. Figure 2. 1 shows the bit error rate performance for the BPSK and DPSK transmission schemes. It is clear that for the bit error rate lower than 10^{-3}, the difference between the performance of the BPSK and DPSK schemes is around 1 dB.
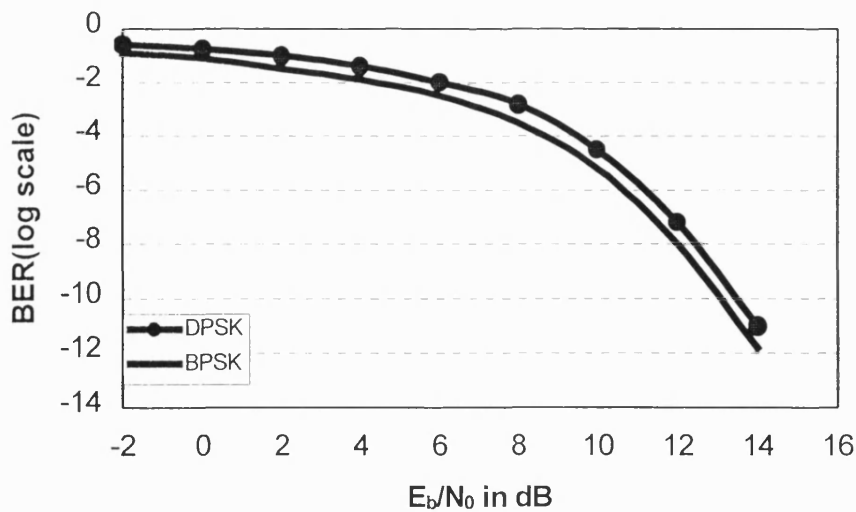
Figure 2. 1: The BER performance of BPSK and DPSK transmission schemes in a Gaussian channel.

In a practical DS-CDMA system, there is co-channel interfering signal and it requires to include the effect of MAI in the BER expression. Omura [2- 19] has derived an expression using the Chernoff bound for the bit error rate of a synchronous DS-CDMA system.

$$P_e \leq \frac{1}{2} e^{-A^2/J_0}$$
(2-8)

In equation **(2-8)**, J_0 is defined as the sum of all interfering cross-correlation terms. As $A^2 = E_b$, the bit energy, this bound is equal to the bit error rate of equation **(2-7)** with the noise power spectral density N_0 replaced by the J_0. Equation **(2-8)** gives the upper bound for the DPSK and the BER for the BPSK scheme should be within 1 dB of this figure as predicted by Figure 2. 1.

2.2.4 The 'Near-Far' Problem in the DS-CDMA System

The 'Near-Far' effect is a phenomenon that limits the performance of the DS-CDMA communication systems. Since it is not possible to make all users signature waveform perfectly orthogonal for all possible delays or in a multipath environment, MAI exists between users. Where other user signals are received at higher power than the desired user's signal, the 'Near-Far' effect occurs and in this case, co-channel interference can overwhelm the desired user signal and the bit error rate performance degrades. Another major source for this phenomenon

is the fading of mobile channels. In this case, if the desired user's signal is fading, even though it is nearer to the receiver than other users, it may be received weaker than the other user signals which are at a greater distance.

Turin [2- 20] has estimated that for an asynchronous DS-CDMA system in a single-path channel and for a BER under 10^{-3}, the maximum number of users is around 20% of the signature waveform length, N, and in the fading channel it falls to only 5%. It means that without using 'Near-Far' resistance receivers, the DS-CDMA scheme is unusable in a mobile channel.

2.3 Multiple-Access Channels' Model for the DS-CDMA System

The structure of a DS-CDMA communication system in general is shown in Figure 2. 2. In the transmitter, the data bits modulate and spread a pseudorandom sequence at one data bit per spreading code word and send it into the transmission channel. The transmission channel may contain static multipath or multipath-fading with Doppler frequency, narrowband interference, other user interference and the additive white Gaussian noise (AWGN).
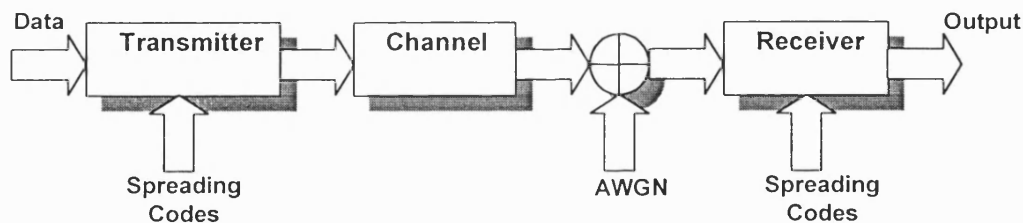
Figure 2. 2: A general structure of a DS-CDMA communication system.

In the receiver, after transferring the received signal to the base-band, the same pseudorandom sequence is used to despread it. A correlator performs this function and after that the output signal of correlator passes through a decision device, which detects the transmitted data bit.

In a multiple-access DS-CDMA environment, K users are transmitting their data simultaneously into the channel. Figure 2. 3 shows the block diagram of this system, which is an asynchronous DS-CDMA system with a BPSK modulation scheme. The system model consists of K

simultaneous users. Each user is assigned a unique signature waveform. The kth user's signature is $c_k(t)$ and consists of bipolar chips of duration T_c. The kth user's transmitted signal is:

$$s_k(t) = \sum_{i=1}^{L} \sqrt{2} b_k(i) c_k(t - iT_b) \cos(\omega_0(t - iT_b) + \theta_k)$$ (2-9)

In equation (2-9), $b_k(i)$ is a polar data bit with amplitude ± 1 and length, T_b, $T_b = NT_c$ where N is the length of the signature sequence in chips, and L is the number of data bits in a data block.
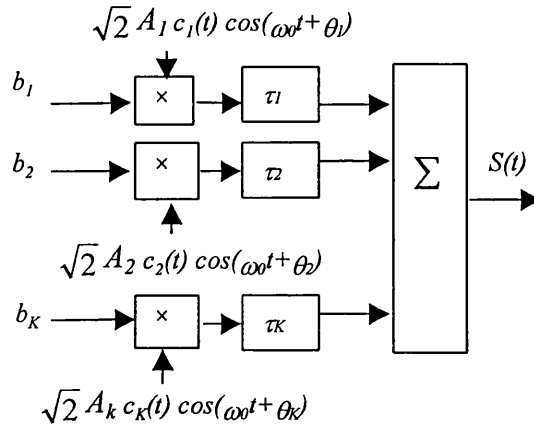
Figure 2. 3: Asynchronous phase-coded DS-CDMA model.

The transmitted signal is of the form:

$$s(t) = \sum_{k=1}^{K} s_k(t - \tau_k)$$ (2-10)

In equation (2-10), τ_k is a random delay that is assumed uniformly distributed over $(0, T_b)$. The demodulated received signal in an AWGN channel is of the form:

$$r(t) = \sum_{k=1}^{K} \sum_{i=1}^{L} A_k(i) b_k(i) c_k(t - iT_b - \tau_k) + n(t)$$ (2-11)

where $A_k(i)$ is the received amplitude of the kth user's signal in the ith data bit and $n(t)$ is the AWGN, with two sided power spectral density of $N_0 / 2$ W/Hz.

In a multipath-fading channel[4], with the time varying impulse response of $h(\tau;t)$, the kth user's received signal is [2- 22]:

$$r_k(t) = \sum_{m=1}^{P} a_m^k(t) e^{j\varphi_m^k(t)} s_k [t - \tau_k - T_m]$$
(2-12)

where

$$h(\tau;t) = \sum_{m=1}^{P} a_m^k(t) e^{j\varphi_m^k(t)} \delta(\tau - T_m)$$
(2-13)

In equation **(2-13)**, P is the number of paths in the channel, T_m is the excess delay of the mth multipath signal, $a_m^k(t)$ and $\varphi_m^k(t)$ are the amplitude and the phase of the mth fading process relative to the kth user. The fading process is taken to be the sum of P complex Gaussian processes, each with a mean value equals to $A_m^k e^{j\Phi_m^k}$ and a variance value equals to $\text{var}_m^k = E[|a_m^k(t) e^{j\varphi_m^k(t)} - A_m^k e^{j\Phi_m^k}|^2]$. In this case, the demodulated received signal in the equation **(2-11)** is changed as below:

$$r(t) = \sum_{k=1}^{K} \sum_{i=1}^{L} A_k(i) b_k(i) [\sum_{m=1}^{P} a_m^k(t) e^{j\varphi_m^k(t)} c_k(t - iT_b - \tau_k - T_m)] + n(t)$$
(2-14)

where L is the number of data bits in a data block. Equation **(2-14)** shows the general form of the received signal in a multiple-access and multipath-fading DS-CDMA environment. In this study, it is assumed that the first user is the desired user and the receiver has knowledge of the propagation delay of the desired signal. In this case τ_l can be set to zero.

2.4 The Conventional Matched Filter Receiver

The conventional matched filter receiver is the simplest receiver, which can be implemented in the DS-CDMA environment to detect the transmitted data. It contains a matched filter that correlates the received signal with the desired user's signature waveform and makes a soft decision of transmitted data. A decision device takes the sign of the soft decision to estimate the

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[4] It will be explained in Appendix B.

transmitted data bit. The conventional matched filter receiver can be analysed in the both the single-user and multi-user DS-CDMA environments. These analyses are useful to understand the basic techniques for detecting the spread spectrum signal and the effect of MAI on the desired user's signal in the multiple-access DS-CDMA environment.

2.4.1 Conventional Matched Filter Receiver in a Single-User Environment

The simplest model of a channel in the DS-CDMA communication system is line-of-sight transmission and a single-user environment. It is assumed that the received signal is corrupted with the additive Gaussian noise and such a channel is termed a Gaussian channel. The received signal contains the desired user's signature and the data bit, as below:

$$r(t) = A_1 b_1 c_1(t) + n(t) \tag{2-15}$$

In equation (2-15), A_1 is a complex constant that shows the amplitude and phase of the line-of-sight propagated signal. The conventional matched filter receiver, which is the optimum maximum-likelihood receiver for this type of channel, convolves the received signal with a local time reversed replica of the desired user's spreading code and takes the sign of result as an estimation of the detected data. Figure 2. 4 shows the structure of the conventional matched filter receiver. As can be seen, the received signal is multiplied by a replica version of the desired user's signature waveform, where perfect synchronisation is assumed. This signature waveform is the same as that is used in the transmitter for the spreading process. The post-correlated signal goes to the BPSK demodulator, which performs the operation of integration over a bit period T_b, sampling the output of the integrator at the bit rate, and making the decision. The sampled data, which represents a soft decision of the transmitted data bit, is passed through a decision unit. This unit takes the sign of the soft estimated data to perform the estimated data bit.
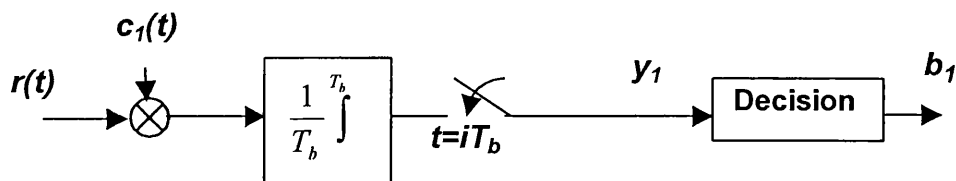
Figure 2. 4: The structure of a conventional matched filter receiver in a single-user Gaussian channel.

In a single-user Gaussian channel, by using the maximum-likelihood criteria, the conventional matched filter receiver is the structure that implements the optimum receiver and has the best BER performance [2- 21]. A typical bit error rate (BER) performance of the conventional matched filter receiver in a Gaussian channel is shown in Figure 2. 5. In this case, the processing gain of the simulated DS-CDMA system is 31 or the length of signature waveform signal is selected 31 chips per bit. This diagram shows the BER performance of the optimum single-user receiver and this represents the limit of the BER performance when the MAI can be completely cancelled from the received signal in a multi-user environment. In other words, it represents the lower bound on the achievable BER performance of a 'Near-Far' resistance receiver in a DS-CDMA environment with the processing gain of 31.

The conventional matched filter receiver has a simple structure and it is very helpful to understand the despreading process in the DS-CDMA channel. As it will be seen, all parts of the conventional matched filter receiver are utilised to implement the RAKE receiver, which is used to collect the scattered rays of propagated signal's energy in the multipath channels. It is noted that the conventional matched filter receiver is equivalent to one branch of the RAKE receiver.
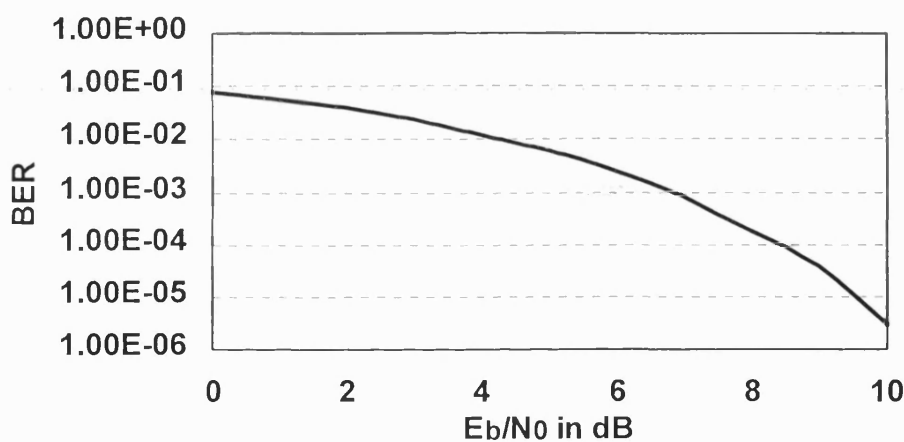
Figure 2. 5: The BER performance of the conventional matched filter receiver in a single-user Gaussian DS-CDMA channel with a processing gain of 31.

2.4.2 Conventional Matched Filter Receiver in a Multi-User Environment

In a synchronous multi-user channel all bits of all users are aligned in time and for simplifying the discussion, it is assumed that all carrier phases are equal to zero. Assuming K direct

sequence users in a synchronous single-path binary phase shift keying (BPSK) channel, the baseband received signal can be expressed as:

$$r(t) = \sum_{k=1}^{K} A_k b_k c_k (t) + n(t) \qquad (2\text{-}16)$$

In equation **(2-16)**, A_k, b_k, and $c_k(t)$ are the amplitude, the data bit, and the signature waveform of the kth user. The power of the kth signal is equal to the square of its amplitude that is assumed to be constant over a bit intervals. In general, the rate of signature waveform signal, $f_c = 1/T_c$ (chip rate), is much greater than the data bit rate, $f_b = 1/T_b$. Multiplication of the BPSK signal at the transmitter by the signature waveform, has the effect of spreading it out in frequency domain by a factor of f_c / f_b, which is called processing gain (PG) and the signature waveform sometimes referred as the spreading code. The conventional matched filter detector for receiving the signal described in the equation **(2-16)**, is performed by using a bank of K correlators or matched filters, as is shown in Figure 2. 6.
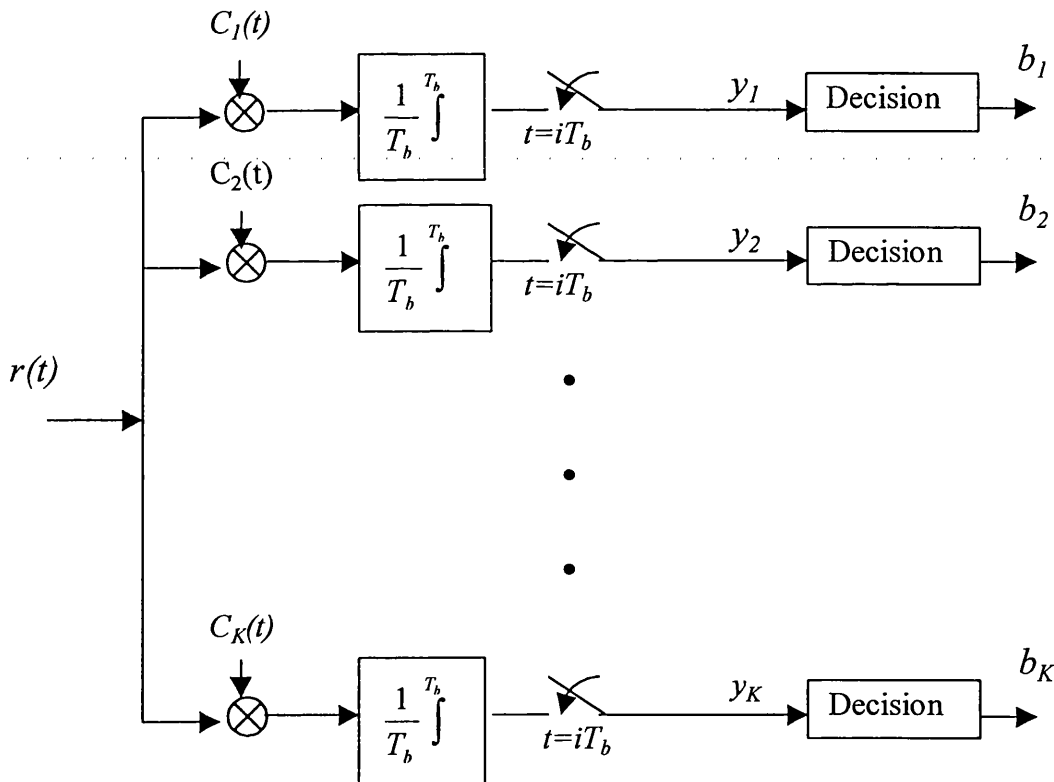
Figure 2. 6: The structure of the conventional matched filter receiver in a multi-user DS-CDMA channel.

In the conventional matched filter receiver, each signature waveform signal is regenerated and correlated with the received signal in a separate detector branch [2- 23]. The outputs of the correlators are sampled separately every sample per bit to provide soft estimation of transmitted data. The final bipolar ± 1 hard data decisions are made according to the sign of the soft estimates.

However the conventional matched filter receiver detects each user's data in each branch of the receiver without regarding to the existence of the other users' signals, the success of this detector depends on the properties of the correlation between signature waveforms. In this situation, the auto-correlation of the signature codes should be much larger than the cross-correlation between them. The cross-correlation of two signature waveform $c_i(t)$ and $c_k(t)$, is defined as:

$$h_{i,k} = \frac{1}{T_b} \int^{T_b} c_i(t) c_k(t) dt \qquad (2\text{-}17)$$

Here, if $i=k$, $h_{kk}=1$, and if $i \neq k$, $0 \leq h_{ik} < 1$. The soft estimate of the kth user's correlator for a particular bit interval is:

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\begin{aligned}
y_k &= \frac{1}{T_b} \int^{T_b} r(t) c_k(t) dt \\
&= A_k b_k + \sum_{\substack{i=1 \\ i \neq k}}^{N} h_{i,k} A_i b_i + \frac{1}{T_b} \int^{T_b} n(t) c_k(t) dt \qquad (2\text{-}18) \\
&= A_k b_k + MAI_k + z_k
\end{aligned}
$$

In other words, correlation with the kth user itself gives rise to the recovered data term, $A_k b_k$, correlation with all the other users gives rise to a term MAI_k, due to multiple access interference and correlation with the thermal noise gives rise to the noise term, z_k.

Since the signature waveforms are generally designed to have very low cross-correlation $(h_{ik} << 1)^5$, the effect of the interfering signal is reduced. As the number of interfering users increases, the amount of MAI increases. Figure 2. 7, which has resulted via computer simulation, shows the effect of increasing the number of co-channel interfering users on the

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[5] It will be explained in Appendix A.

BER performance of the conventional matched filter receiver in a multi-user DS-CDMA environment.
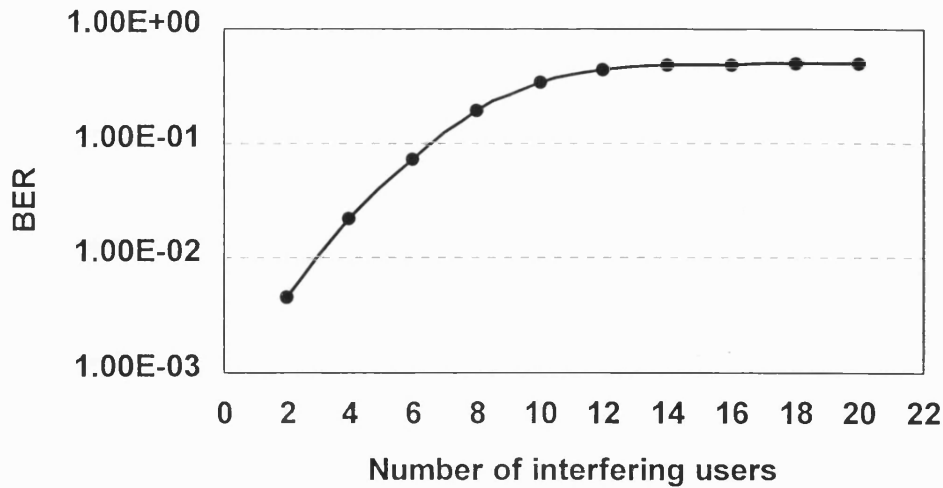
Figure 2. 7: The BER performance of the conventional matched filter receiver versus the number of co-channel users in a 'Near-Far' multiple-access DS-CDMA channel.

In this case, it is assumed that the energy per bit of each interfere user signal is 6 dB more than the energy per bit of the desired user's signal, which shows the 'Near-Far' problem in the channel. As can be seen, by increasing the number of active users in the channel, the BER performance of the conventional matched filter receiver degrades.

In addition, the presence of strong users with large amplitudes can affect the performance of the detecting process. In this situation, the stronger users may overwhelm the weaker user. This is known as the 'Near-Far' problem and may happen in the situation of fading or different geographical location of transmitters. The result in Figure 2. 8, which has been achieved via computer simulation, shows the effect of the 'Near-Far' problem on the BER performance of the conventional matched filter receiver. In this case, the DS-CDMA channel contains 10 co-channel users and the $E_{b(desired)}/N_0 = 6$ dB. As is shown, by increasing the energy of co-channel users' signals, the desired user's signal is overwhelmed by the strong MAI and the BER performance of the conventional matched filter receiver is degraded.
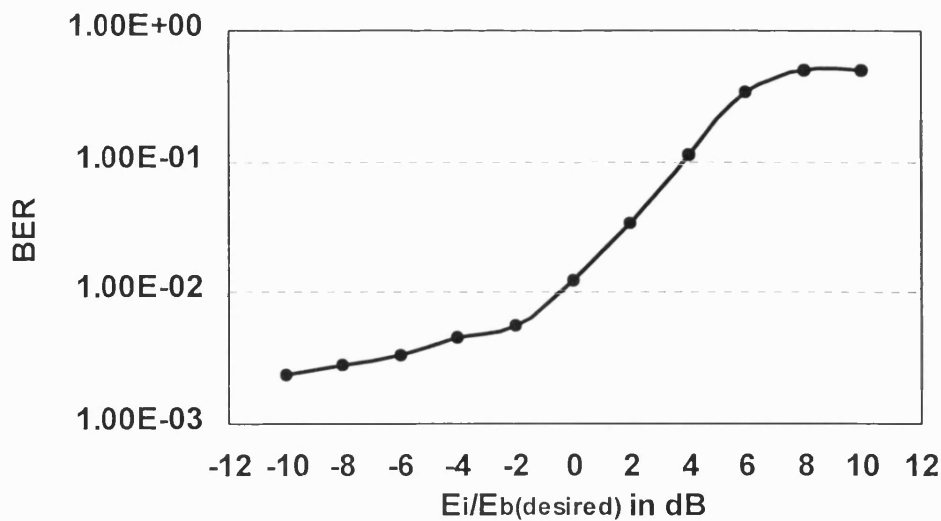
Figure 2. 8: The BER performance of the conventional matched filter versus $E_i/E_{b(desired)}$ in a 10-user 'Near-Far' multiple-access DS-CDMA channel.

There are some techniques that can be used to improve the performance of the conventional matched filter receiver in a multi-user environment with 'Near-Far' effect. Signature waveform design, using power control, error correction coding and utilising adaptive antennas are part of these techniques that can be used to reduce the effect of MAI on the performance of the conventional matched filter receiver.

♦ **Signature waveform design**: The first approach is aimed at the design of spreading signature waveforms with good cross-correlation property [2- 24]. Ideally, if the codes were all orthogonal, then $h_{ik}=0$, and there would not be any MAI. However, in practice most channels contain some degree of asynchronism, it is not possible to design codes that are orthogonal over all possible delays.

♦ **Power control**: The use of power control ensures that all users' signals arrive with the same amplitude to the receiver and there is not any strong user to overwhelm another one [2- 25].

♦ **Error correction coding**: The design of error correcting codes is another technique that can improve the performance of the conventional matched filter receiver in the DS-CDMA channel with low signal to interference ratio condition.

♦ **Adaptive antenna**: By using an adaptive antenna, the desired user signal and a fraction of MAI, which are in the desired direction, are enhanced and the reminder of the MAI that arrive from other directions will be attenuated.

2.5 The Optimum Maximum-Likelihood Receiver

In the multi-user DS-CDMA environments, some parameters of the transmitted signals such as signature waveform, timing, amplitude and phase may be jointly used to increase the performance of receivers to detect transmitted signals. In this case, one of the most important assumption which is realistic for the base-station but it is unrealistic for the handsets in a mobile environment, is that the receiver knows the signature waveform of all users.

Making the assumption that all parameters in a DS-CDMA environment are available to the system, Verdu [2- 2] proposed and analysed the optimum multi-user or maximal-likelihood sequence detector. Although this receiver has the best performance of all the receivers in the DS-CDMA environment, it is currently too complex to be implemented in the practical systems in real time. Nevertheless, the performance of the maximum-likelihood receiver is a good reference for comparing the performance of other sub-optimal receivers. As it has been said, the maximum-likelihood receiver has the best performance for the price of using all additional information and high implementation complexity and the conventional matched filter receiver has the poorest performance with a simple implementation structure.

2.5.1 Mathematical Background of the Maximum-Likelihood Receiver

The optimum receiver is defined as the receiver that maximises the probability of making a correct decision based on the observation of the received signal. The optimum receiver in a multi-user DS-CDMA environment is defined as the receiver that selects the most probable sequence of bits $\{b_k(n),\ 1 \leq k \leq K,\ 1 \leq n \leq L\}$ given the received signal $r(t)$ observed over the time interval $0 \leq t \leq LT_b + 2T_b$ [2- 23] where K and L are the number of users and the number of bits in one block of data respectively . For a synchronous mode of data transmission, one symbol of each user interferes with the desired user's symbol. Hence in this situation, it is sufficient to consider the received signal in the time interval $0 \leq t \leq T_b$. Over this interval and in the AWGN, the received signal in multi-user DS-CDMA environment is:

$$r(t) = \sum_{k=1}^{K} A_k c_k(t) b_k + n(t)$$ (2-19)

In this case, the optimum receiver is defined as the receiver that selects the vector of the most probable data bits for each user $\{b_k, 1 \le k \le K\}$ given the received signal $r(t)$ observed over the time interval $0 \le t \le T_b$ [2- 2]. This decision criterion is called the maximum *a posteriori* probability (MAP) criterion. Some simplification occurs in the MAP criterion when the transmitted signals are all equally probable *a priori*. In this case, the decision criterion is equivalent to maximising the $f[r(t)|s(t)]$, which is the conditional probability density function of the observed signal given $s(t)$. The conditional probability density or any monotonic function of it is called the likelihood function and the decision criterion based on the maximum of $f[r(t)|s(t)]$, is called the maximum-likelihood criterion. It is clear that under the assumption of equal *a priori* probability for the transmitting signals, the receiver based on the MAP criterion is the same as the receiver based on the maximum-likelihood criterion.

The maximum-likelihood criterion in the multi-user DS-CDMA environment is equivalent to computing the log-likelihood function or distance metrics, $\Lambda(\mathbf{b})$, and selecting the data bits $\{b_k, 1 \le k \le K\}$ that minimise $\Lambda(\mathbf{b})$. In a synchronous multi-user DS-CDMA environment, the log-likelihood function is formed as below:

$$\Lambda(\mathbf{b}) = \int_0^{T_b} \left[r(t) - \sum_{k=1}^{K} A_k c_k(t) b_k \right]^2 dt$$ (2-20)

In equation (2-20), $\mathbf{b}$ represents the data bits from the K users. By expanding the equation (2-20), is obtained:

$$\Lambda(\mathbf{b}) = \int_0^{T_b} r^2(t) dt - 2 \sum_{k=1}^{K} A_k b_k \int_0^{T_b} r(t) c_k(t) dt + \sum_{j=i}^{K} \sum_{k=1}^{K} A_j A_k b_j b_k \int_0^{T_b} c_k(t) c_j(t) dt$$ (2-21)

In equation (2-21), the integral involving $r^2(t)$ is common to all possible sequences $\{b_k\}$ and it may be ignored in the computation of the log-likelihood function. The term $\int_0^{T_b} r(t) c_k(t) dt, 1 \le k \le K$, which represents the cross-correlation of the received signal with each of the K users signature waveform, can be substituted by y_k and the integral involving $c_k(t)$, $c_j(t)$ is simplify to h_{jk}. Therefore the equation (2-21) can be expressed as a modified log-likelihood function as below:

$$D'(\mathbf{Y_K}, \mathbf{b_K}) = -2\sum_{k=1}^{K} A_k b_k y_k + \sum_{j=1}^{K}\sum_{k=1}^{K} A_k A_j b_k b_j h_{j,k} \qquad (2\text{-}22)$$

It is noted that selecting the sequences $\{b_k\}$ that minimise $D'(\mathbf{Y_K}, \mathbf{b_K})$ is equivalent to selecting the sequences $\{b_k\}$ that maximise the metric $C(\mathbf{Y_K}, \mathbf{b_K}) = -D'(\mathbf{Y_K}, \mathbf{b_K})$. In this case, the maximum-likelihood criterion can be expressed in the form of correlation metrics:

$$C(\mathbf{Y_K}, \mathbf{b_K}) = 2\sum_{k=1}^{K} A_k b_k y_k - \sum_{j=1}^{K}\sum_{k=1}^{K} A_k A_j b_k b_j h_{j,k} \qquad (2\text{-}23)$$

It is observed that the maximum-likelihood receiver, for implementing the equation (2-23) and computing the correlation metrics, should have knowledge of the all users received signal amplitudes. It has to compute the correlation metrics for all 2^K possible choices of the bits in the bit set of K users and select the sequence that gives the largest correlation metrics.

In summary, for the synchronous mode of operation of a DS-CDMA system, the maximum-likelihood receiver is implemented by using equation (2-23). It has a structure, which consists of a bank of K correlators or matched filters followed by a detector that computes the 2^K correlation metrics and selects the sequence corresponding to the largest correlation metrics.

In the asynchronous mode of the multi-user DS-CDMA system, there are exactly two consecutive symbols from each co-channel user that overlap a desired user's symbol. In this case, the maximum-likelihood receiver computes the log-likelihood function, which is formed as below:

$$\Lambda(\mathbf{b}) = \int_0^{LT_b + 2T_b} \left[r(t) - \sum_{k=1}^{K} A_k \sum_{i=1}^{L} b_k(i) c_k(t - iT_b - \tau_k) \right]^2 dt \qquad (2\text{-}24)$$

The integral involving $r^2(t)$ may be ignored, since it is common to all possible information sequences. Therefore, it is observed that the log-likelihood function may be expressed in terms of a correlation metric that involves the outputs $\{r_k(i), \ 1 \le k \le K, \ 1 \le i \le L\}$ of KL correlators or matched filters. If a block processing approach is adopted, the maximum-likelihood receiver must compute 2^{KL} correlation metrics to determine the K block of sequences, each of which has a length, L. This approach is too complex to be implemented in practice because K and L are generally large. In this case, the Viterbi algorithm is used to implement the maximum-

likelihood criterion. The Viterbi algorithm uses the fact that each transmitted symbol overlaps at most with $2K$-2 symbols [2- 23]. Although a significant reduction in the computational complexity is obtained with respect to the block size parameter, L, the exponential dependence on the number of users cannot be reduced. Figure 2. 9 shows the structure of the optimum maximum-likelihood receiver.

Received Signal → Matched Filter Bank → Viterbi Algorithm (Maximum - likelihood detector) → Detected Bit
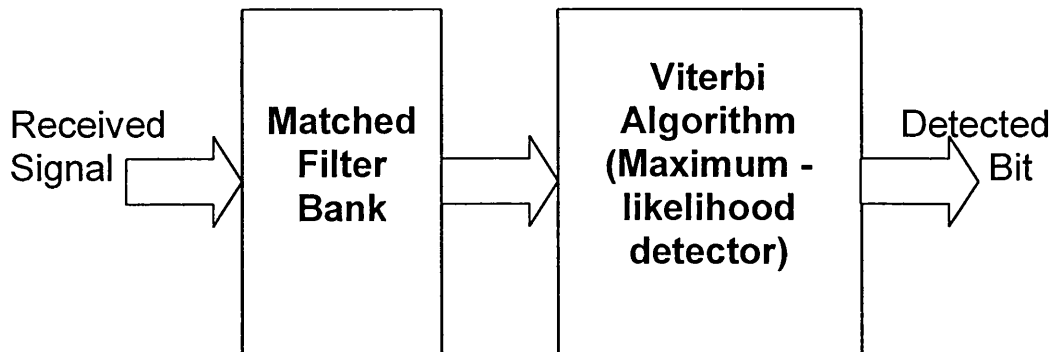
Figure 2. 9: The structure of the maximum-likelihood receiver in a multi-user DS-CDMA environment.

2.5.2 The Performance Evaluation of the Maximum-Likelihood Receiver

To observe the huge difference between the performance of the maximum-likelihood and conventional matched filter receivers in a DS-CDMA multiple-access environment, it is useful to compare the performance of the two described receivers. In this way, by using Monte Carlo simulation techniques, a multi-user DS-CDMA channel with the 'Near-Far' effect is simulated. This channel contains five interfering users, where the power of each co-channel user's signal is 5 dB higher than the power of the desired user's signal. As is known, these two described receivers have a marginal BER performance in this environment, where the maximum-likelihood receiver has the best performance and the conventional matched filter has the poorest performance in the multi-user DS-CDMA environment.

The BER performances of two receivers in different channel model scenarios are shown in Figure 2. 10 and Figure 2. 11. Figure 2. 10 shows the BER performance of the maximum-likelihood and the conventional matched filter receivers as a function of E_b/N_0 in a 5-user 'Near-Far' multiple-access interference channel with $E_i/E_{b(desired)} = 5$ dB.
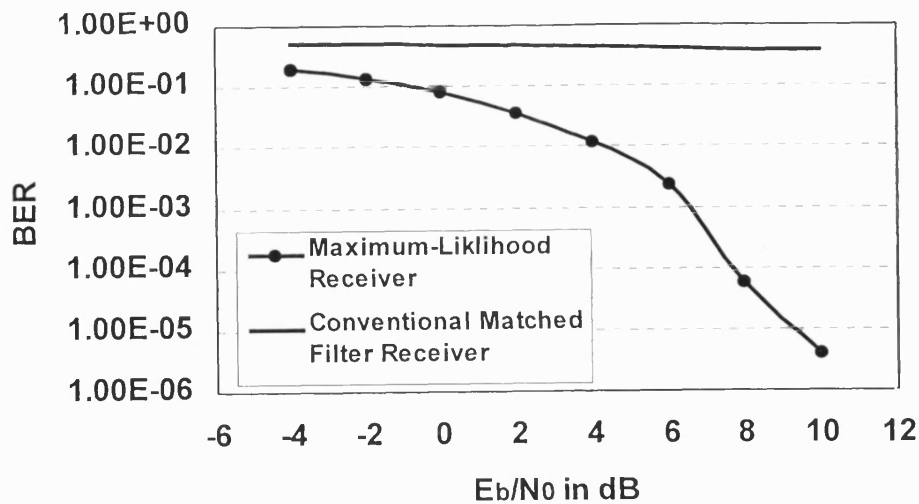
Figure 2. 10: The BER performance of the maximum-likelihood and the conventional matched filter receivers versus E_b/N_0 in a 5-user 'Near-Far' multiple-access DS-CDMA environment.

Figure 2. 11 shows the BER performance of the two receivers as a function of $E_r/E_{b(desired)}$ in a 5-user 'Near-Far' multiple-access DS-CDMA channel with $E_{b(desired)}/N_0$ =5 dB. As can be seen, there is a significant difference between the BER performance of the two receivers under the different conditions. It is shown that the conventional matched filter receiver is very sensitive to the power of co-channel interfering users and by increasing the power of the interfering users, a huge degradation will occur in the BER performance of this receiver. On the other hand, the performance of the maximum-likelihood receiver is not sensitive to the 'Near-Far' effect and the BER performance of this receiver remains approximately constant by increasing the power of co-channel interfere users.

In the maximum-likelihood receiver, the notable performance gains over other types of receivers are obtained because of [2- 2]:

♦ The signature waveform of all users is be known.

♦ The received amplitude of all users is be known.

♦ The timing of all users is be acquired.

♦ Exponential complexity in the number of users.

♦ A centralised structure that demodulates all transmitters.
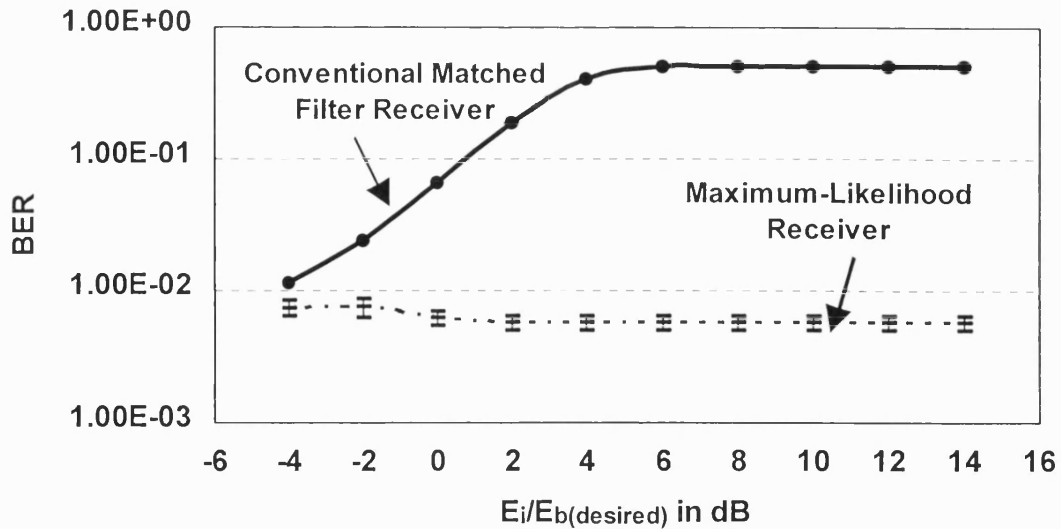
Figure 2. 11: The BER performance of the maximum-likelihood and the conventional matched filter receivers versus $E_i/E_{b(desired)}$ in a 5-user 'Near-Far' multiple-access DS-CDMA environment (the error bars show 95% confidence limits assuming normal distribution).

As has been said before, under the assumption of access to all the parameters in a DS-CDMA environment, which is realistic for the base-station but unrealistic for handsets in a mobile environment, the performance of the maximum-likelihood receiver is the best performance among all of receivers.

2.6 Sub-optimum DS-CDMA Receivers

In the previous section, it has been shown that the optimum maximum-likelihood receiver for detecting the data in a multi-user DS-CDMA channel requires all information about timing, signature waveform and amplitude of users' signals and also that it has a complexity that grows exponentially with the number of users. Some other types of receiver, which are called sub-optimum receivers, have complexities that grow linearly with the number of users.

The conventional matched filter receiver is the simplest sub-optimum receiver, which has a complexity that grows linearly with the number of users, but for combating the effect of MAI and 'Near-Far' problem, such a receiver requires some type of power control for it to be effective. There are some other types of sub-optimum receiver with implementation

complexities that grow linearly with the number of co-channel users and performances, which are better than the performance of the conventional matched filter receiver in the DS-CDMA multiple-access environments. The decorrelating detector and the MMSE receiver are two well-known types of sub-optimum receivers, which will be described in following sub sections.

2.6.1 The Decorrelating Detector

The decorrelating detector is a sub-optimum receiver, which has a linear computational complexity with regard to the number of co-channel users and it can significantly reduce the effect of co-channel interference in the multi-user DS-CDMA environments [2- 3], [2- 4]. Equation (2-18), which shows the output of the kth matched filter, can be rewritten for all K users in the multi-user channel as:

$$y_1 = \sum_{i=1}^{K} h_{i,1} A_i b_i + z_1 \, , \; y_2 = \sum_{i=1}^{K} h_{i,2} A_i b_i + z_2 ,..., \; y_K = \sum_{i=1}^{K} h_{i,K} A_i b_i + z_K \qquad (2\text{-}25)$$

By using a matrix-vector format, the above equations may be rewritten as below:

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ \vdots \\ y_K \end{bmatrix} = \begin{bmatrix} 1 & h_{2,1} & \cdots & \cdots & h_{K,1} \\ h_{1,2} & 1 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ h_{K,1} & \cdots & \cdots & \cdots & 1 \end{bmatrix} \begin{bmatrix} A_1 & 0 & \cdots & \cdots & 0 \\ 0 & A_2 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & 0 \\ 0 & \cdots & \cdots & 0 & A_K \end{bmatrix} \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ \vdots \\ b_K \end{bmatrix} + \begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ \vdots \\ z_K \end{bmatrix} \qquad (2\text{-}26)$$

or:

$$\mathbf{Y = H. A. b + Z} \qquad (2\text{-}27)$$

In equation (2-27), **b** is the data vector, **Z** is a noise vector, and **Y** is the output vector of the matched filter bank. **A** is a $K \times K$ diagonal matrix that contains the received signal amplitudes and **H** is a $K \times K$ correlation matrix, where it's elements represent the value of the cross-correlation of each pair of the signature waveforms of K users. For example, h_{ik} shows the cross-correlation value of the ith and the kth user signature waveforms. Since $h_{ik}=h_{ki}$, **H** is symmetric and invertible for the synchronous systems [2- 4].

The decorrelating detector estimates the transmitted data bits by applying the inverse of the correlation matrix, **H**, to the output of the matched filter bank, **Y**. The estimated data at the output of the decorrelating receiver is:

$$\hat{b}_{dec} = Sgn\ (\mathbf{H}^{-1}\ \mathbf{Y}\ ) = Sgn\ (\mathbf{A}\ \mathbf{b} + \mathbf{H}^{-1}\ \mathbf{Z}\ ) = Sgn\ (\mathbf{A}\ \mathbf{b} + \mathbf{Z}_{dec}) \qquad (2\text{-}28)$$

As can be seen, the decorrelating receiver completely eliminates the effect of co-channel interference or MAI in the multi-user DS-CDMA environments and hence its performance is independent of the power of co-channel other user's signals. It means that the decorrelating detector is a 'Near-Far' resistant receiver[6] [2- 4]. The operation of this detector is very similar in concept to the zero-forcing equaliser [2- 23] that is used to eliminate inter-symbol-interference (ISI) in the digital communication systems. The structure of the decorrelating receiver in the multi-user DS-CDMA system is shown in Figure 2. 12.
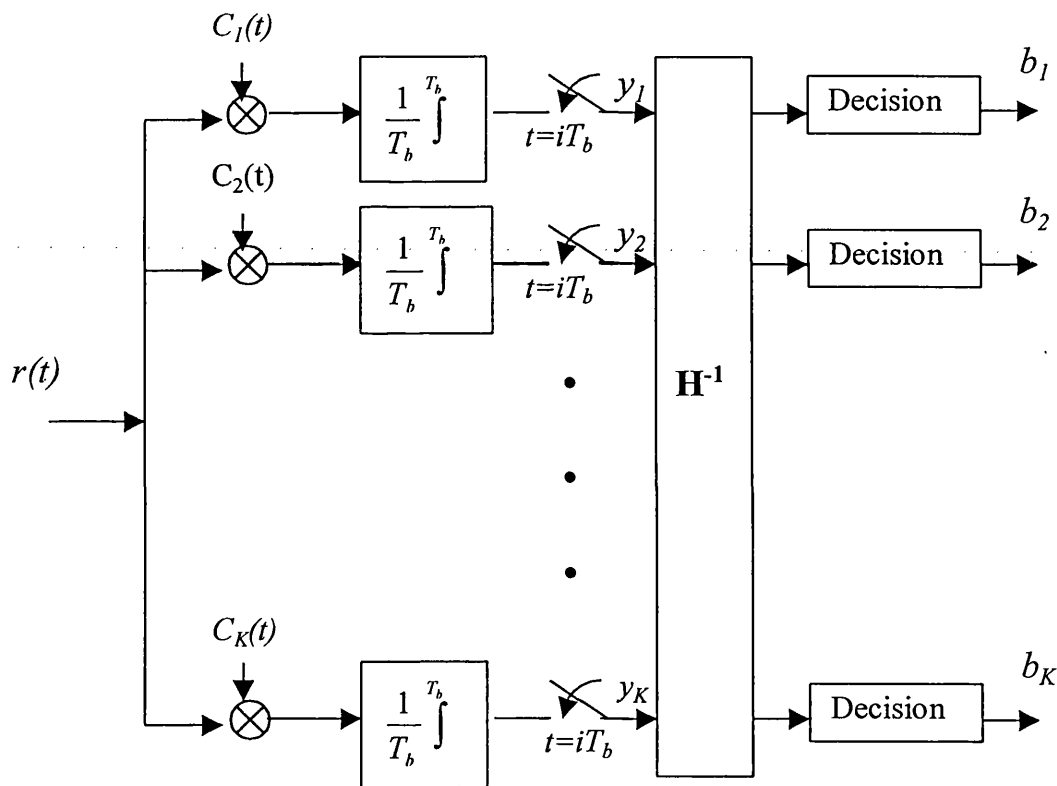
Figure 2. 12: The structure of the decorrelating detector.

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[6] The 'Near-Far' resistance is defined as the ability of receiver to resist against the powerful unwanted users' signal when the power of AWGN approaches to zero.

As can be seen, the received signal is passed through a matched filter bank, where each of the matched filters in the bank is matched to one signature waveform. In this case, the inverse of the correlation matrix, $\mathbf{H}^{-1}$, decorrelates the output of matched filter bank and K decision devices take the sign of results to estimate the K transmitted data bits.

The performance of the decorrelating receiver will be evaluated and compared with other multi-user DS-CDMA receivers in chapter six.

The main advantages of the decorrelating receiver, as a sub-optimum receiver in the DS-CDMA system, may be summarised as below:

♦ Provides substantial performance and capacity gain over the conventional matched filter receiver.

♦ It does not need to estimate the received signal's amplitudes.

♦ Its computational complexity is linear in the number of users and is lower than the maximum-likelihood receiver.

♦ It is the maximum-likelihood solution in the absence of any knowledge about the received signal's amplitudes.

The bit error rate performance of the decorrelating receiver is independent of the interfering signals' amplitudes. This property makes the decorrelating detector a 'Near-Far' resistant receiver.

In the decorrelating detector, the notable performance gains over the conventional matched filter receiver are obtained because of [2- 19]:

♦ The signature waveform of all users should be known.

♦ The timing of all users is be acquired.

♦ The matrix inverse $\mathbf{H}^{-1}$ is computed in real time.

A disadvantage of this detector is that it causes noise enhancement. The power of the noise term $\mathbf{Z}_{dec}=\mathbf{H}^{-1}\mathbf{Z}$ at the output of the decorrelating receiver, referring to equation (2-28), is always greater than the power of the noise term, $\mathbf{Z}$, at the output of the conventional matched filter receiver. Another disadvantage of the decorrelating detector is the difficulty of computing the inverse of $\mathbf{H}$ in the real time. For example in an asynchronous mode, $\mathbf{H}$ is of order $K \times L$ that is large for a typical message length, L.

2.6.2 The Minimum Mean Square Error (MMSE) Receiver

In the pervious section, it was shown that the decorrelating detector, which is a sub-optimum receiver, is able to delete the effect of co-channel interference. Also, it has a good performance in the 'Near-Far' DS-CDMA environments and hence it is known as a 'Near-Far' resistance receiver. In some special situations, when the power of all the interfering signals are very weak, the BER performance of the decorrelating detector may be worse than the BER performance of the conventional matched filter receiver. This is because, by applying the inverse of the correlation matrix, H^{-1}, in the output of matched filter bank to perform the decorrelating detector, the noise term is enhanced. This enhancement for the case of the weak co-channel interference, degrades the BER performance of the decorrelating receiver in compare with the conventional matched filter receiver. In this situation, a receiver that takes into account the power of the co-channel interference in comparison with the background noise is useful.

The minimum mean square error (MMSE) receiver is a linear detector that takes into account the background noise [2- 10]. This detector implements the linear transformation, $b=LY$, where the matrix L is to be determined in accordance with the requirement to minimise, $J(b)$, the mean square error between the actual transmitted data and the output of the matched filter bank:

$$J(b)=E[\,|\,b\text{-}LY\,|^{2}]$$

(2-29)

It is easily shown that the optimum choice of L that minimises $J(b)$ is [2- 23]:

$$L=(H+\frac{1}{2}N_0A^{-2})^{-1}$$

(2-30)

In this case, the output of detector is:

$$\hat{b}_{mmse} = Sgn\;[(H+\frac{1}{2}N_0A^{-2})^{-1}Y]$$

(2-31)

In equation (2-31), H is the correlation matrix of the signature waveforms, A is a diagonal matrix related to received signal's amplitudes, and $N_0/2$ is the power spectral density of noise. It is clear that the conventional matched filter receiver, the decorrelating detector, and the MMSE receiver are linear detectors of the form:

$$\hat{b} = Sgn \ [\mathbf{LY}] \tag{2-32}$$

where $\mathbf{L}$ is a $K \times K$ matrix, which implements the linear transformation. In the conventional matched filter receiver $\mathbf{L}$ is a diagonal unique matrix, in the decorrelating detector $\mathbf{L}=\mathbf{H}^{-1}$ and in the MMSE receiver $\mathbf{L}$ has the value that is shown in equation (2-30). As can be seen, the MMSE detector implements a modified inverse of the correlation matrix compared to the decorrelating receiver, which is proportional to the noise. The MMSE detector balances the desire to eliminate MAI completely with the desire not to enhance background noise. When the energy of the noise, N_0, in comparison with the diagonal elements of $\mathbf{H}$, is small, the MMSE detector approaches the performance of the decorrelating detector. When the noise level is high however, the detector ignores the presence of MAI and approaches to the conventional matched filter receiver.

The BER performance of the MMSE detector is generally better than the BER performance of the decorrelating receiver and this is because it takes into account the background noise. If $N_0 \to 0$, the MMSE detector approaches to the decorrelating receiver and therefore the 'Near-Far' resistance of this detector is the same as the 'Near-Far' resistance of the decorrelating receiver[7]. Although the implementation complexity of the MMSE detector is slightly more than the implementation complexity of the decorrelating receiver (because it requires to track the received signal amplitudes), it has an advantage that makes it an interesting receiver. The advantage of the linear MMSE detector is that it can easily be implemented in an adaptive form with training sequences[8]. In this case, it does not require any information relating to the signature waveform of co-channel interfering users nor the received signal's amplitudes. The structure of an adaptive MMSE detector is shown in Figure 2. 13.

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[7] As it has been seen in section 2.6.1, the decorrelating detector is a 'Near-Far' resistance receiver.

[8] The adaptive implementation and the performance of the MMSE detector will be considered in chapters 3 and 6 respectively.
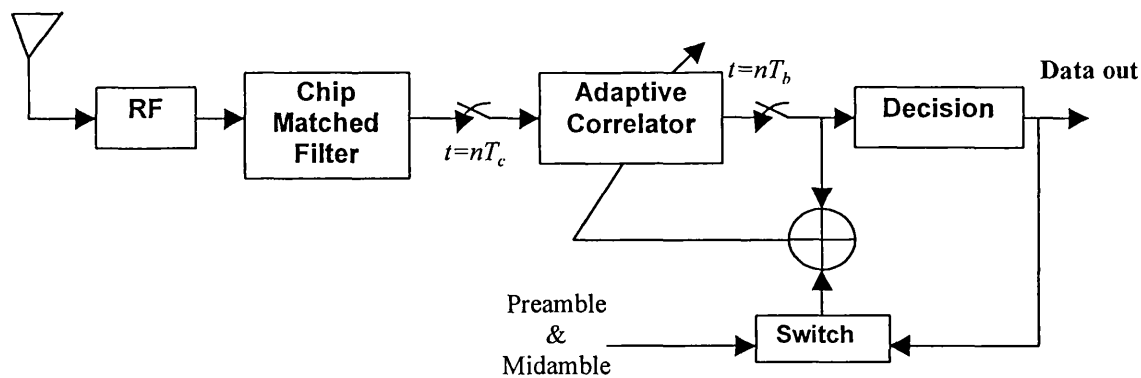
Figure 2. 13: The structure of an adaptive MMSE receiver.

As is shown in Figure 2. 13, after converting the received signal to the baseband, it passes through a chip-matched filter and is sampled at the end of every chip interval. These samples are fed into the adaptive finite impulse response (FIR) digital filter. The structure of this filter is a transversal filter, which comprises a taped delay line and a summer. The values of the tap weights in this filter determine the impulse response of the filter and to implement an adaptive filter, they are adjusted via an adaptive algorithm. The output of the filter is sampled once every bit interval and hard-limited to form the estimated value of the received data. If the filter coefficients were adjusted to have the same values corresponding to the chips of the signature waveform of the desired user, the structure and performance of this receiver would be the same as the conventional matched filter receiver. In this case, If the desired signal has been received in the presence of the AWGN only, its performance would be good as the performance of the maximum-likelihood receiver in a Gaussian channel. In the presence of co-channel interference, the adaptive nature of the MMSE receiver changes the tap weights of the transversal filter in the sense of minimum mean square error for preventing interference and noise.

The adaptive implementation of the MMSE receiver has the following characteristics and properties [2- 18]:

♦ The training sequence of the desired user should be known.

♦ The received signal's amplitudes need not to be known or estimated.

♦ The signature waveforms of other co-channel users need not be known.

♦ Knowledge of the signature waveform of the desired user is not necessary but it is useful for initialising the adaptive algorithms.

♦ It can be implemented in an asynchronous channel and in this situation it requires the timing of the desired user be acquired.

◆ The timing of other co-channel users need not be acquired.

Due to the simple structure and good characteristics, the adaptive MMSE receiver attracts much attention to be implemented in the future cellular and personal communication systems. Many researchers investigated the performance of the adaptive MMSE receiver. Madhow and Hoing [2- 26], Rapajic and Vucetic [2- 27], Miller[2- 28], [2- 29], [2- 30], Pateros and Saulnier [2-31], Yoshida and *et al* [2- 32] proposed this receiver for use in the DS-CDMA systems.

Chapter three considers the adaptive MMSE receiver in the DS-CDMA environment. It investigates the abilities of the adaptive MMSE receiver for despreading the DS-CDMA signals, combating the effect of interference and using multipath phenomena of channel for diversity reception in the DS-CDMA system. The performance evaluation of this receiver via computer software simulation will be considered in chapter six.

2.7 Artificial Neural Network Structures as DS-CDMA Receivers

In the multiple-access DS-CDMA environment, the co-channel other users' signals degrade the performance of the receiver to detect the desired user signal. In this situation, the desired user's signal is embedded in the AWGN and MAI. Thus, the boundaries formed between optimal decision regions are non-linear. A particularly interesting method of multi-user detection, which has the potential for low computational complexity, is the application of neural network concepts.

The topology of a neural network contains a large amount of interconnection of simple computing cells referred to as 'neurons' or 'processing units'. These non-linear units are able to provide non-linear boundaries in the decision region, which divide the decision region into optimal sub-regions. In most common networks, neurons are arranged in layers with the input data fed to the network at the input layer. The data then passes through the network to the output layer to provide the solution or answer.

The computing power of the neural network structures is high because of its parallel-distributed structure and its ability to learn and therefore generalise. These two information-processing capabilities enable artificial neural networks to solve complex problems.

Two common structures of the neural network topology, which are suitable for use in the DS-CDMA environment, are the adaptive multi-layer perceptron (MLP) and the recurrent neural network. The adaptive MLP neural network, which is implemented as an adaptive detector, contains several layers in its feedforward structure. It can be used as an adaptive single-user receiver, such as adaptive MMSE receiver, in the multiple-access DS-CDMA environment. The recurrent neural network receiver contains some feedback loops in its structure. These feedback loops provide some kind of memory in the network and make it as a dynamic system. This structure has the potential to be used as a multi-user detector in the DS-CDMA environment.

2.7.1 The Adaptive Multi-Layer Perceptron Neural Network Receiver

It has been noted that designing the adaptive systems that self-tune the detector parameters from the observation of the received signals in the multiple-access environment is a very interesting way to implement the DS-CDMA receivers. The multi-layer topology of the neural network potentially has this ability to work as the adaptive receivers in this environment. They have the ability to perform subtle decision boundaries via the training process to separate the wanted and unwanted signals. For this purpose, the multi-layer perceptron are trained to demodulate DS-CDMA waveforms. The training is an iterative process of modifying interconnection weights and thresholds of neurons to minimise an error function. The structure of the adaptive MLP neural network DS-CDMA receiver is shown in Figure 2. 14. As can be seen, the MLP neural network contains the input, the hidden and the output layers, the connections between which are assigned interconnection weights. The details and the performance evaluation of this receiver will be considered in chapters four and six respectively.

(Input Nodes)

(Hidden Nodes)

(Output Node)

Output

r(t)

Tapped

Delay

Line
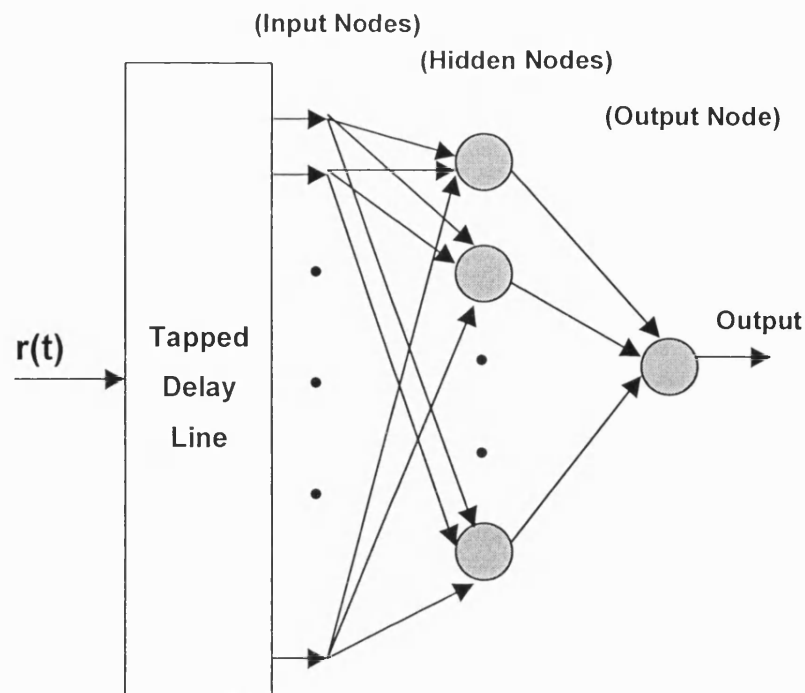
Figure 2. 14: The structure of an adaptive MLP neural network DS-CDMA receiver.

2.7.2 The Recurrent Neural Network Receiver

To implement a multi-user DS-CDMA receiver by using the structure of the recurrent neural network, the received signal is passed through a bank of matched filters. The number of matched filters in the filter bank is equal to the number of users in the multi-user channel. The output signals of the matched filters are sampled and are fed into the recurrent neural network structure. The recurrent neural network has a structure that consists of a number of small non-linear processing units. Each unit contains a summer and a non-linear function. The output of each unit is fed to all other units via connection weights and each unit has an external input. Figure 2. 15 shows the structure of the recurrent neural network multi-user receiver, which has been used to detect the data bits of K co-channel users in the DS-CDMA environment. The details and the performance evaluation of this receiver will be considered in chapters four and six respectively.

$C_I(t)$

$C_2(t)$

$r(t)$

$C_K(t)$

$$\frac{1}{T_b}\int^{T_b}$$

$$\frac{1}{T_b}\int^{T_b}$$

$$\frac{1}{T_b}\int^{T_b}$$

$t=iT_b$ y_1

$t=iT_b$ y_2

$t=iT_b$ y_K

Recurrent Neural Network

Decision b_1

Decision b_2

Decision b_K
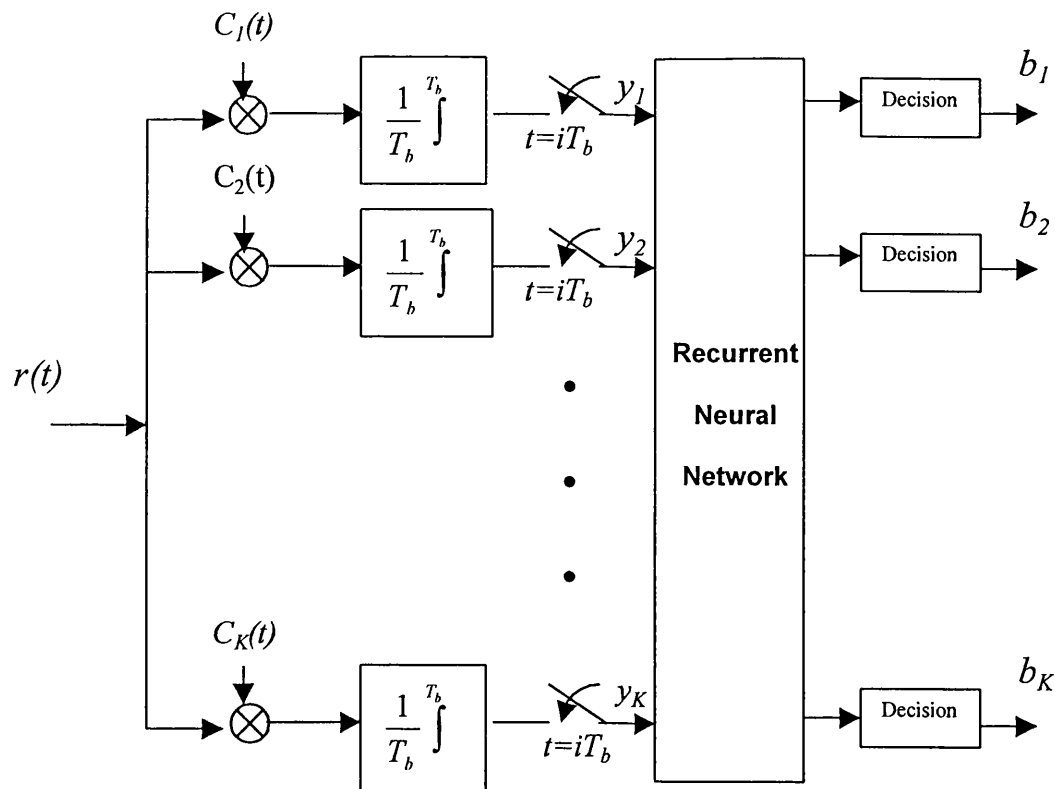
Figure 2. 15: The Structure of the recurrent neural network receiver in a DS-CDMA environment.

2.8 Summary

In this chapter, the main structures for implementing the receiver in the multiple-access DS-CDMA communication system have been investigated. It has been shown that the co-channel interference or MAI is a major problem, which degrades the performance of the receivers in DS-CDMA multiple-access channels. In this case, it is needed to use the receiver with the ability of resisting the 'Near-Far' effect. It has been shown that the performance of the conventional matched filter receiver, which is the simplest receiver among other DS-CDMA detectors, degrades by increasing the power of co-channel users in the multiple-access environment. This shows that the resistance of the conventional matched filter receiver in the DS-CDMA environment with 'Near-Far' effect is very poor. However the maximum-likelihood receiver has the best performance among other receivers in this environment and is a 'Near-Far' resistance receiver but its implementation complexity grows exponentially with the number of users. On the other hand, it requires additional information about timing, signature waveform

and amplitude of users' received signals and hence it is not suitable to be implemented in the commercial environments.

Sub-optimum receivers which have the implementation complexities that grow linearly with the number of users, are suitable candidates to be used as DS-CDMA receivers. The decorrelating detector and the MMSE receiver are two most famous types of these receivers. It has been shown that the decorrelating detector, which uses the inverse of the correlation matrix in its structure, is a 'Near-Far' resistance receiver and eliminates the effect of co-channel interference on the received signal. The great advantage of the linear MMSE detector is that it can easily be implemented in an adaptive form with training sequences. In this case, it does not require any information related to the signature waveform of co-channel interfering users and the received signal's amplitudes.

The neural network structures are alternative candidates for use as receivers in the DS-CDMA environment. In this case, two common topologies, in the name of multi-layer perceptron and the recurrent neural network are used to implement the DS-CDMA receivers. The advantages of the neural network receivers to draw non-linear boundaries between the wanted signal and unwanted signals in the decision domain, makes these receivers attractive for use as DS-CDMA receivers in the future systems.

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Chapter Three

Adaptive MMSE Receiver in DS-CDMA System

3.1 Introduction

As has been described in the previous chapter, the maximum-likelihood receiver, which has the best performance among DS-CDMA receives, is a 'Near-Far' resistant receiver. However its implementation complexity in comparison with the conventional matched filter receiver is high, and it requires a large amount of additional information about the received signals for it to operate in a DS-CDMA multiple-access environment. This required information consists of amplitude, phase, timing and signature waveform sequence of different co-channel users, which should be known or estimated by the receiver. In order to achieve practical receivers with lower implementation complexity, various types of sub-optimum receivers have been proposed. These receivers are designed to achieve the performance near the performance of the maximum-likelihood receiver with reduced implementation complexity but all of them require several additional information that may be difficult to obtain in a multiple-access DS-CDMA channel. However it is common for a receiver to have knowledge of the signature waveform, but the amplitude, phase and timing are dynamic parameters and must be tracked and updated during the real data transmission. In addition, in the mobile system environment, the mobility of the handset receiver and the nature of the mobile radio channel creates multipath-fading resulting in a rapid rate of fluctuations in the amplitude and phase of the received signal. Hence, an effective and important way of rejecting multiple-access interference in a DS-CDMA communication environment is the design of adaptive detectors, which self-tune the detectors' parameters from the observation of the received signals [3- 1]. In recent years, adaptive receivers have attracted considerable attentions as a way of detecting the DS-CDMA signals in the multi-user and multipath environments.

One important type of the adaptive 'Near-Far' resistant DS-CDMA receiver, which avoids some of the mentioned problems, is the adaptive minimum-mean-squared-error (MMSE) receiver. As has been considered in chapter two, the MMSE receiver can be implemented adaptively in a DS-CDMA environment. In this case, it acts as a single-user detector, which requires no additional information more than the code timing of the desired user and has relatively low implementation complexity in comparison with the maximum-likelihood receiver.

A large amounts of research has been done by Madhow and Hoing [3- 2], [3- 3], Rapajic and Vucetic [3- 4], Miller[3- 5], [3- 6], [3- 7], Pateros and Saulnier [3- 8], [3- 9], and Yoshida and *et al.* [3- 10] related to the adaptive MMSE receiver. It has been shown that this detector is a

'Near-Far' resistant receiver in the multiple-access DS-CDMA environments and can produce significant performance improvement in the presence of MAI, multipath channel and narrow band interference. In this way, Miller [3- 5] has shown that using the MMSE receiver with no power control can double the capacity of a CDMA network in comparison with using the conventional matched filter receiver with perfect power control. Pateros and Saulnier [3- 9] have shown that the MMSE receiver is robust to both narrowband and static multipath interference and finally Madhow and Hoing [3- 3] tried to use several techniques to reduce the implementation complexity of this receiver.

However, the adaptive MMSE receiver does not operate sufficiently well in the dynamic multipath-fading channels such as mobile environments. In this situation, the adaptation speed of the receiver is too slow to allow the parameters to be tracked in a fast varying channel and the adaptive MMSE receiver loses phase lock on the desired user's signal and the BER performance of the receiver degrades rapidly. Miller [3- 11] has investigated the behaviour of the MMSE receiver in the flat fading environment and proposed a modification to the structure of this receiver for combating the effect of losing phase lock on the desired user in deep fading.

This chapter considers the basis and applications of the adaptive MMSE receiver in the DS-CDMA communication systems. In this way, a low complexity adaptive MMSE receiver is considered and its performance is evaluated for different channel model scenarios. A new modification will be proposed for helping the adaptive MMSE receiver to function in the multipath-fading mobile channels. In this case, this receiver is able to despread the desired user's signal, reject the MAI, and combat the effect of multipath-fading channel. The simplicity of the adaptive MMSE receiver's structure and good performance makes it attractive for use in both base-station and mobile handset in the future mobile system.

The reminder of this chapter is organised as follows: In the following section, the adaptive algorithms that are used to implement the adaptive receiver for detecting the desired user's signal, are investigated. The third section lays out the background and signal model in the DS-CDMA environment. The main structure of the adaptive MMSE receiver is the subject of the fourth section. The modification to the structure of the adaptive MMSE receiver for improving the receiver's performance in the multipath-fading channel is considered in the fifth section and the summary of the chapter comes in the final section.

3.2 Adaptive Algorithms

To develop a recursive method for updating the weights of the adaptive transversal filter which is used to implement the adaptive systems, an optimum solution of the linear filtering problem is required. The result is called the Wiener-Hopf solution and can be achieved directly by minimising a parameter called the mean square error. By subtracting the actual output signal of the filter from the desired value, the error signal is performed. A well-known algorithm is issued by modifying the Wiener-Hopf equations using the method of steepest descent and deriving an estimate for the gradient vector. This algorithm is known as the Least-Mean-Square (LMS) algorithm and is highly popular and widely used in a variety of applications. Another recursive algorithm is the Recursive Least-Squares (RLS) algorithm, which is derived from the Least-Squares (LS) algorithm and is based on a basic result in the linear algebra known as the matrix-inversion lemma [3- 13].

The LMS and RLS algorithms are the best known adaptive algorithms to be implemented in a variety of different adaptive systems applications. The LMS algorithm allows for a simple implementation but it has a slow convergence speed. The RLS algorithm converges much faster than the LMS algorithm but requires special conditions and more computational power to be implemented and it can become unstable.

3.2.1 The Wiener Filter

A class of optimum linear discrete-time filters are known as Wiener filters. The purpose of implementing the Wiener filter is to produce an optimum estimate of a wanted signal corrupted with noise. To illustrate the basic mathematics behind the Wiener filter, consider Figure 3. 1. In this figure $\mathbf{X}$ is the input vector and $\mathbf{W}$ is the linear filter weight vector. Also $y(n)$ is the output of the filter, $d(n)$ is the desired value, and $e(n)$ is the estimation error at time n. The linear filter is performed as a transversal filter, which contains N taped-delay line in its structure.

The error signal, $e(n)$, is expressed as $e(n) = d(n) - y(n)$, that is:

$$e(n) = d(n) - W^T X = d(n) - \sum_{i=0}^{N-1} w_i x_{k-i} \qquad (3-1)$$
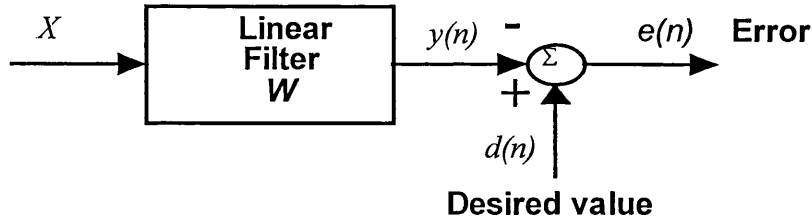
Figure 3. 1: The basic structure of Wiener filter.

In equation **(3-1)**, X and W are defined as:

$$X = \begin{bmatrix} x_k \\ x_{k-1} \\ \vdots \\ x_{k-(N-1)} \end{bmatrix} \quad , \quad W = \begin{bmatrix} w_0 \\ w_1 \\ \vdots \\ w_{N-1} \end{bmatrix}$$

The square value of the error is given as:

$$e^2(n) = d^2(n) - 2d(n)X^T W + W^T X X^T W \tag{3-2}$$

The mean square error is given by taking the expectation value of both sides of equation **(3-2)** and therefore is expressed as:

$$J = E[e^2(n)] = E[d^2(n)] - 2E[d(n)X^T W] + E[W^T X X^T W] \tag{3-3}$$

$$= E[d^2(n)] - 2P^T W + W^T R W$$

where $P = E[d(n)X]$ is the cross correlation vector and $R = E[XX^T]$ is the $N \times N$ auto-correlation matrix. Differentiating equation **(3-3)** to find the minimum value of J gives:

$$dJ/dW = -2P + 2RW = 0 \quad \Rightarrow \quad W_{opt} = R^{-1}P \tag{3-4}$$

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The minimum mean-squared error, from equations (3-3) and (3-4), equals:

$$J_{min} = E[d^2(n)] - P^T W_{opt} \qquad (3\text{-}5)$$

As can be seen in the equation (3-4), computing the optimum weight vector requires *a priori* knowledge of the statistical information about the data. This information includes the auto-correlation matrix of the input signal and the cross-correlation vector between the input signal and the desired value.

3.2.2 The Steepest-Descent Algorithm

The steepest-descent algorithm is one of the oldest methods of optimisation, which provides a method of searching on a multi-dimensional surface. To find the minimum value of the mean-squared error, J_{min}, an initial weight for the weight vector should be chosen. By computing the gradient vector $\nabla(J(n))$ at time n, the updated value of the weight vector at time $n+1$ is computed by using the recursive relation as below:

$$W(n+1) = W(n) + \mu [- \nabla(J(n))] \qquad (3\text{-}6)$$

In equation (3-6), μ is a positive real-valued constant, which is called step-size parameter and determines the rate of convergence. It has been shown that the gradient vector $\nabla(J(n))$ is given by [3- 13]:

$$\nabla(J(n)) = -2P + 2RW(n) \qquad (3\text{-}7)$$

In equation (3-7), $P = E[d(n)X]$ is the cross correlation vector and $R = E[X X^T]$ is the $N \times N$ auto-correlation matrix as before. By substituting the result of equation (3-7) in equation (3-6), the recursive relation for updating the weight vector is giving below:

$$W(n+1) = W(n) + 2\mu [P - RW(n)] \qquad n = 0, 1, 2, \ldots \qquad (3\text{-}8)$$

As can be seen, for updating the weight vector toward to the optimum point via the recursive algorithm, the statistical parameters of the data should be known.

3.2.3 The Least-Mean-Square (LMS) Algorithm

The LMS algorithm is an important member of the family of stochastic gradient-based algorithms. The LMS algorithm is designed to approximate the Wiener solution for the optimum filter coefficients. A significant feature of the LMS algorithm is its simplicity and this property has made it the standard among adaptive algorithms. It does not require measurement of the correlation functions or matrix inversion as in Wiener solution. The development of this algorithm is based on the steepest descent algorithm, but unlike the steepest descent method, the LMS algorithm does not require prior knowledge of the statistical parameters of data.

In real situations exact measurement of the gradient vector in equation (3-7) is not possible because it requires prior knowledge of R and P. Therefore the gradient vector must be estimated from the available data. It means the weight vector is updated with an algorithm, which adapts to the incoming data. One such algorithm is the LMS algorithm.

The simplest estimation of R and P are instantaneous estimation of these parameters that is based on the input and the desired values.

$$R(n)=X(n)X^T(n) \quad and \quad P(n)= X(n)d(n) \tag{3-9}$$

According to these estimations, the new recursive relation for updating the weight vector will be as [3- 13]:

$$W(n+1)=W(n)+ 2\mu X(n) [d(n) - y(n)] \tag{3-10}$$

In equation (3-10), $y(n)$ is the output of filter at time n and $d(n) - y(n)$ can be substituted as $e(n)$, the error value at time n.

$$W(n+1)=W(n)+ 2\mu X(n) e(n) \tag{3-11}$$

Equation (3-11) defines the LMS algorithm as an iterative procedure. It adjusts the transversal filter's weights from sample to sample in such a way that minimises the mean square error. In equation (3-11), $W(n+1)$ is the new filter's coefficient, μ is the step-size coefficient that controls the rate and stability of adaptation algorithm and has a value in the range $0 < \mu < 1$, $X(n)$ is the input data, and $e(n)=d(n) - y(n)$ is the value of error signal at time n.

It is important to notice that the performance of the LMS algorithm depends on the value of the step-size parameter, μ, which determines the speed of convergence. By increasing the value of step-size parameter, the speed of convergence increases but the final value of the mean square error and the probability of instability increases. Reduction in the value of the step-size parameter decreases the speed of convergence and the value of steady state mean square error. There are a few factors that influence the value of μ, but in general it should be chosen such that the following conditions are satisfied [3- 13]:

♦ $0 < \mu < 2/\lambda_{max}$, where λ_{max} is the maximum eigenvalue of the correlation matrix R.

♦ The weight vector approaches to the Wiener solution as the number of iteration increases.

♦ The final (steady state) value of MSE is finite.[1]

The main drawback of this algorithm is its slow convergence property and its sensitivity to the value of step-size parameter, μ.

3.2.4 Normalised Least-Mean-Square (NLMS) Algorithm

As is clear from equation (3-11), in the LMS algorithm, the correction term, $\mu\, X(n)\, e(n)$, applied to the filter's weight vector $W(n+1)$ at time $n+1$ is directly proportional to the value of the input vector, $X(n)$. Therefore, when $X(n)$ is large, the LMS algorithm has an increased speed of convergence and hence experiences a gradient noise amplification problem. The NLMS algorithm, which is a modification of the ordinary LMS algorithm, is a way to overcome this problem. In the NLMS, the correction term applied to the filter's weight vector $W(n+1)$ at time $n+1$ is normalised with the squared norm of the tap input vector $X(n)$ at time n as below:

$$W(n+1) = W(n) + 2\,\frac{\tilde{\mu}}{\left\lVert X\,(n)\right\rVert^2}\,X(n)\,e(n) \qquad (3-12)$$

Following observations can be seen in comparing equation (3-12) for the NLMS algorithm and equation (3-11) related to the LMS algorithm [3- 13]:

♦ The adaptation constant, $\tilde{\mu}$, for the NLMS algorithm is dimensionless, but the adaptation constant, μ, for the LMS algorithm has the dimension of inverse power.

---

[1] There are always some residual errors.

◆ With $\mu(n) = \dfrac{\tilde{\mu}}{\|X(n)\|^2}$, the NLMS algorithm is similar to a LMS algorithm with a time varying step-size parameter.

◆ The step-size parameter, $\tilde{\mu}$, in the NLMS algorithm should satisfy the following condition [3- 14] and [3- 15]:

$$0 < \tilde{\mu} < 2 \tag{3-13}$$

It is noted, when the value of the input vector *X(n)* is small, numerical difficulty may arise. To overcome this problem, we can modify the equation **(3-12)** as below:

$$W(n+1) = W(n) + 2\,\frac{\tilde{\mu}}{a + \|X(n)\|^2}\,X(n)\,e(n) \tag{3-14}$$

In equation **(3-14)**, *a > 0*, is a positive parameter that prevents the numerical difficulty to arise. The value of step-size parameter is $0 < \tilde{\mu} < 2$ as before.

3.2.5 The Complex Form of the LMS Algorithm

The complex form of the LMS algorithm is used in the several applications of adaptive linear systems. In this situation the input vector contains complex values and hence the weight vector is located in a complex multi-dimensional space. The complex form of the LMS algorithm is as below [3- 16]:

$$W(n+1) = W(n) + 2\mu\,X^\varsigma(n)\,e(n) \tag{3-15}$$

In equation **(3-15)**, *Xς(n)* is the complex conjugate of *X(n)*, which shows the input vector.

3.2.6 Least-Squares (LS) Algorithm

Another class of optimum linear discrete-time filters known as Least-Squares (LS) Algorithm. The Least-Squares (LS) Algorithm produces an optimum estimate of a wanted signal corrupted with noise via minimising a cost function, $\mathcal{E}(n)$. To illustrate the basic mathematics behind the

Least-Squares (LS) Algorithm, consider Figure 3. 2. In this figure *x(i)* is the input, *y(i)* is the output, and **W** is the linear filter weight vector.
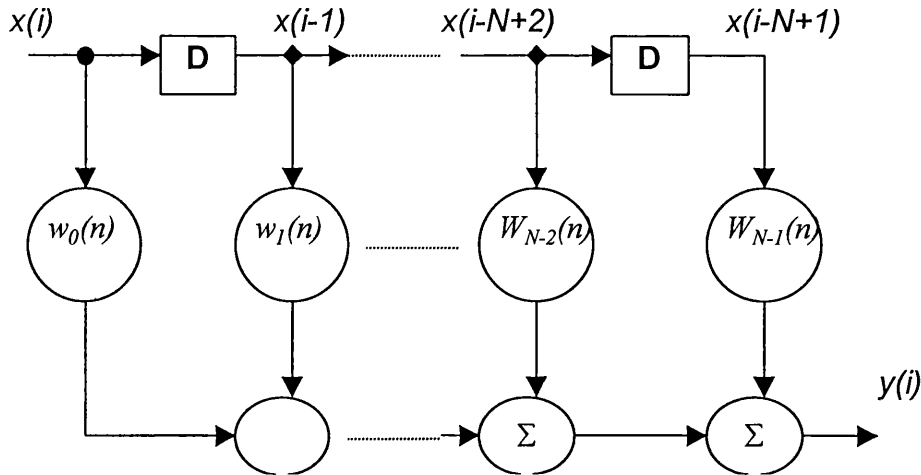
Figure 3. 2: The structure of a transversal filter.

In Figure 3. 2, **D** shows a unit delay cell. The cost function $\mathcal{E}(n)$, will be minimised where *n* is the variable length of the observed data. By introducing a weighting or forgetting factor, $\beta(n,i)$, the cost function is as below:

$$\mathcal{E}(n) = \sum_{i=1}^{n} \beta(n,i) |e(i)|^2 \tag{3-16}$$

In equation (3-16), $e(i)=d(i)-y(i)$ is the error and the weight factor, $\beta(n,i)$, has the property that:

$$0 < \beta(n,i) \leq 1, \qquad i=0, 1, 2, \ldots, n \tag{3-17}$$

The forgetting factor has an exponential form as below:

$$\beta(n,i) = \lambda^{n-i}, \qquad i=0, 1, 2, \ldots, n \tag{3-18}$$

In equation (3-18), λ is a positive constant close to, but less than one. The inverse value of $1-\lambda$ is a measure of the memory of the recursive algorithm. In the special case of $\lambda=1$, the memory of the algorithm is infinity.

The optimum value of the filter's weight vector for minimising the cost function $\mathcal{E}(n)$, is as below [3- 13]:

$$W(n) = \Phi^{-1}(n)\ \Theta(n) \tag{3-19}$$

In equation **(3-19)**, $\Phi(n)$ is the $N \times N$ correlation matrix and $\Theta(n)$ is the $N \times 1$ vector, which shows the cross-correlation between input and the desired value are defined as:

$$\Phi(n) = \sum_{i=1}^{n} \lambda^{n-i} X(i)X^T(i) \tag{3-20}$$

$$\Theta(n) = \sum_{i=1}^{n} \lambda^{n-i} X(i)d(i) \tag{3-21}$$

To compute the least-square estimate of the filter's weight vector, it is required to invert the correlation matrix. This technique is not practical and particularly if the number of weights, N, in the vector is high,

3.2.7 The Recursive Least-Squares (RLS) Algorithm

The RLS algorithm, like the LMS algorithm, is designed to get a recursive algorithm for finding the optimum value of the filter's weight vector. In other words, the RLS algorithm is the recursive implementation of Least-Squares (LS) algorithm. The main aim of using the RLS algorithm is to avoid having to continually compute the matrix inversion required in the LS method.

In recursive implementations of the method of least squares, equations **(3-20)** and **(3-21)** can be rewritten in a new form as below [3- 13]:

$$\Phi(n) = \lambda\ \Phi(n-1) + X(n)X^T(n) \tag{3-22}$$

$$\Theta(n) = \lambda\ \Theta(n-1) + X(n)d(n) \tag{3-23}$$

By using the matrix inversion lemma, the inverse of correlation matrix can be written as [3- 13]:

$$\Phi^{-1}(n) = \lambda^{-1}\Phi^{-1}(n-1) - \frac{\lambda^{-2}\Phi^{-1}(n-1)X(n)X^T(n)\Phi^{-1}(n-1)}{1 + \lambda^{-1}X^T(n)\Phi^{-1}(n-1)X(n)}$$ (3-24)

By defining *P(n)*= $\Phi^{-1}(n)$, *K(n)*= *P(n) X(n)*, and *α(n)=d(n)-W(n-1)X(n)*, the recursive least-squares algorithm is derived as below:

$$K(n)=[\lambda^{-1}P(n-1)X(n)]/[1+\lambda^{-1}X^T(n)P(n-1)X(n)]$$

$$\alpha(n)=d(n)-W^T(n-1)X(n)$$ (3-25)

$$W(n)=W(n-1)+K(n)\alpha(n)$$

$$P(n)=\lambda^{-1}P(n-1)-\lambda^{-1}K(n)X^T(n)P(n-1)$$

In equation (3-25), *P(n)* is an $N \times N$ square matrix with zero initial values, *X(n)* is the input signal vector, and λ is the forgetting factor whose value ranges from 0.98 to 1.0. The computation is started with a known initial condition *P(0)*=$\delta^{-1}I$, where δ is a small positive constant and *I* is an identity $N \times N$ matrix. The initial value for filter's weight vector is *W(0)*=0 and the new data samples are employed for updating the old estimated parameters by using recursive relations in equation (3-25).

The RLS algorithm converges faster than the LMS algorithm and therefore it is suitable for time varying channels. The major problem with this algorithm is the large computational complexity involved, which increases with the order of filter and it imposes a limit on the maximum filter order employed in practice. Also, its performance is so sensitive to the value of the forgetting factor and the optimum performance demands when the best value is chosen for the forgetting factor. This value changes with the conditions so it has to be re-calculated and this is difficult in the dynamic environments. There is more comprehensive coverage of the LMS and RLS algorithms in [3- 13] and [3- 17].

It should be noted that fast RLS algorithms could not be used in our special application. This is because it takes advantage of a cyclic relationship between the contents of the equaliser at successive sampling times. That cyclic relationship is not present in our DS-CDMA receiver system due to the fact that the output of the filter is not sampled at the same rate that the input is clocked.

3.3 The Background and Signal Model in a DS-CDMA System

As has been shown in chapter two, the demodulated received signal in a multi-user AWGN channel is of the form:

$$r(t) = \sum_{k=1}^{K}\sum_{i=1}^{L} A_k(i)b_k(i)c_k(t - iT_b - \tau_k) + n(t) \tag{3-26}$$

where $A_k(i)$ is the received amplitude of the kth user's signal in the ith data bit and $n(t)$ is the Additive White Gaussian Noise (AWGN), with a power spectral density of $N_0/2$ W/Hz. In a multipath-fading channel, with time varying impulse response of $h(\tau;t)$, the kth user's received signal is [3- 18]:

$$r_k(t) = \sum_{m=1}^{P} a_m^k(t)e^{j\varphi_m^k(t)}s_k[t - \tau_k - T_m] \tag{3-27}$$

where

$$h(\tau;t) = \sum_{m=1}^{P} a_m^k(t)e^{j\varphi_m^k(t)}\delta(\tau - T_m) \tag{3-28}$$

In equation (3-27), P is the number of paths in the multipath channel, T_m is the excess delay of the mth multipath signal, $a_m^k(t)$ and $\varphi_m^k(t)$ are the amplitude and the phase of the mth fading process relative to the kth user. The fading process is taken to be the sum of P complex Gaussian processes, each with a mean value equals to $A_m^k e^{j\Phi_m^k}$ and a variance value equals to $\text{var}_m^k = E[|a_m^k(t)e^{j\varphi_m^k(t)} - A_m^k e^{j\Phi_m^k}|^2]$. In this case, the demodulated received signal in the equation (3-26) is changed as below:

$$r(t) = \sum_{k=1}^{K}\sum_{i=1}^{L} A_k(i)b_k(i)[\sum_{m=1}^{P} a_m^k(t)e^{j\varphi_m^k(t)}c_k(t - iT_b - \tau_k - T_m)] + n(t) \tag{3-29}$$

Equation (3-29) shows the general form of the received signal in a multiple-access and multipath-fading environment. In this thesis, it is assumed that the first user is the desired user and the receiver has knowledge of the propagation delay of the desired signal. In this case, τ_1 can be set to zero.

After converting the received signal to the baseband, it is passed through a chip-matched filter and sampled at the end of every chip interval. During each bit interval, the N sampled chips are accumulated and stored in a received vector. It is assumed that the rate of fading is slow so that the amplitude and phase of the received vector are constant during a bit. In this case, it can be shown that [3-19]:

$$r\ (i) = b_1\ (i)\sum_{m=1}^{P} a_m^1\ (t)e^{j\varphi_m^1(t)}c_{1,m} + \sum_{k=2}^{K}\frac{A_k}{A_1}J_{k,i}[\sum_{m=1}^{P} a_m^k\ (t)e^{j\varphi_m^k(t)}c_{k,m}] + N_i \qquad (3\text{-}30)$$

In equation (3-30), $J_{k,i}$ is a factor that depends on the other users' data and signature waveforms, and the noise vector, N_i, consists of independent samples from a Gaussian noise process during the ith bit interval. Also $c_{1,m}(t)=c_1(t\text{-}T_m)$ and $c_{k,m}(t)=c_k(t\text{-} iT_b \text{-} \tau_k\text{-}Tm)$. The simplest channel for a DS-CDMA communication system is a line-of-sight transmission and single-user environment. This is the well-known Gaussian channel and the received vector signal contains the desired user's signature and data bit as below:

$$r(i) = Ab_1\ (i)c_1 + N_i \qquad (3\text{-}31)$$

In equation (3-31), A is a complex constant that shows the amplitude and phase of line-of-sight propagation. The conventional matched filter receiver that is the optimum maximum-likelihood receiver in this condition, correlates the received vector for the ith bit with a local replica of the desired user's spreading code.

$$\hat{b}_1\ (i) = \text{sgn}\ \{\text{Re}\ [\ c_1^H\ r\ (i)\ ]\ \} \qquad (3\text{-}32)$$

In equation (3-32), the superscript H indicates '*Hermitian Transposition*' that means conjugate transposition. In a static multipath single-user channel, the values of $a_m^1(t)$ and $\varphi_m^1(t)$ are constant and the received vector is as below:

$$r\ (i) = b_1\ (i)\sum_{m=1}^{P} a_m^1 e^{j\varphi_m^1}c_{1,m} + N_i \qquad (3\text{-}33)$$

In this situation, the well-known RAKE receiver that is the optimum receiver in this condition, collects the different rays of propagated energy in the multipath channel. In this case, the impulse response of the receiver's filter is equal to the complex conjugate of the channel impulse response.

$$h_r(t) = \sum_{m=1}^{P} a_m^1 e^{-j\varphi_m^1} \delta(t - T_m) \tag{3-34}$$

To implement the RAKE receiver, it is needed to determine the amplitudes and phases of different rays in the multipath channel that can be estimated by channel sounding techniques. In a single-user and flat fading channel, $a_m^1(t)=0$ and $\varphi_m^1(t)=0$ for $m>1$. In this case, the received vector contains the desired user's signature and data bit as below:

$$r\,(i) = a_1^1(t)e^{j\varphi_1^1(t)}b_1(i)c_1 + N_i \tag{3-35}$$

In this situation, the receiver should track the phase of received signal and compensate it to remove the effect of changing phase on the signal detection process. The conventional matched filter receiver detects the data bit as below:

$$\hat{b}_1(i) = \mathrm{sgn}\!\left(\mathrm{Re}\!\left[e^{-j\varphi_1^1(t)} c_1^H r(i) \right] \right) \tag{3-36}$$

As indicated in equation (3-36), the receiver must remove the effect of changing phase on the desired user's signal. In a single-user and multipath-fading channel, the received signal contains a collection of different propagation rays that each ray passed through an independent fading path sub-channel. In this case, the received vector is as below:

$$r\,(i) = b_1(i)\sum_{m=1}^{P} a_m^1(t)e^{j\varphi_m^1(t)}c_{1,m} + N_i \tag{3-37}$$

In this situation, a receiver with a RAKE combiner structure detects the received data. Equation (3-38) shows the detection process of this receiver.

$$\hat{b}_1(i) = \mathrm{sgn}\!\left(\mathrm{Re}\!\left[\sum_{m=1}^{P} a_m^1(t)e^{-j\varphi_m^1(t)} c_{1,m}^H r(i) \right] \right) \tag{3-38}$$

To implement this structure for the receiver to combat the effect of multipath-fading channel, it requires to know or to estimate the delay profile and attenuation coefficients of the time varying multipath channel. One of the most popular estimating techniques is the maximum-ratio

combining (MRC), which can be used with a simple alpha tracker [3- 18] to estimate the multipath channel parameters. This algorithm requires a short time window to form an estimate and has low complexity. Separate alpha trackers are used to estimate the in-phase and the quadrature components of the complex channel impulse response. In the next sections, this technique will be employed to modify the structure of the adaptive MMSE receiver in the multi-user and multipath-fading channel.

The performance of the conventional matched filter receiver and the RAKE receiver will be evaluated in the chapter six via Monte Carlo simulation. However these detectors have good performance in the single-user channels, but they can lead to substantially degraded performance in the presence of MAI in the multi-user channels.

3.4 The Adaptive MMSE Receiver

The dynamic nature of communication channel in the DS-CDMA systems degrades the performance of the fixed detector, especially in a multi-user 'Near-Far' environment. The adaptive receivers that 'self-tune' the detector parameters from the observation of the received signal, are suitable candidates for use in such environments. The detection process of these receivers is based on 'one-shot', i.e., receivers that form the decision of the ith bit of the kth user as the sign of a function of the received signal observed only during the ith bit interval. These types of receivers have a measure of 'Near-Far' resistance and can produce significant performance improvements in the presence of MAI, multipath channels and narrow band interference. One of the most suitable receivers in this class is the adaptive MMSE receiver that is shown in Figure 3. 3.

After converting the received signal to the base-band, it is passed through a chip-matched filter and sampled at the end of every chip interval. After that, the signal is fed into the adaptive finite impulse response (FIR) transversal filter. In ordinary situations, the number of taps in the transversal filter is equal to the period of the signature waveform. The output of the filter is sampled once every bit interval and hard-limited to form the estimate of the received data. The tap weights are updated once every bit interval and an error signal that is the difference between the desired signal and the output of the adaptive filter controls the updating process.
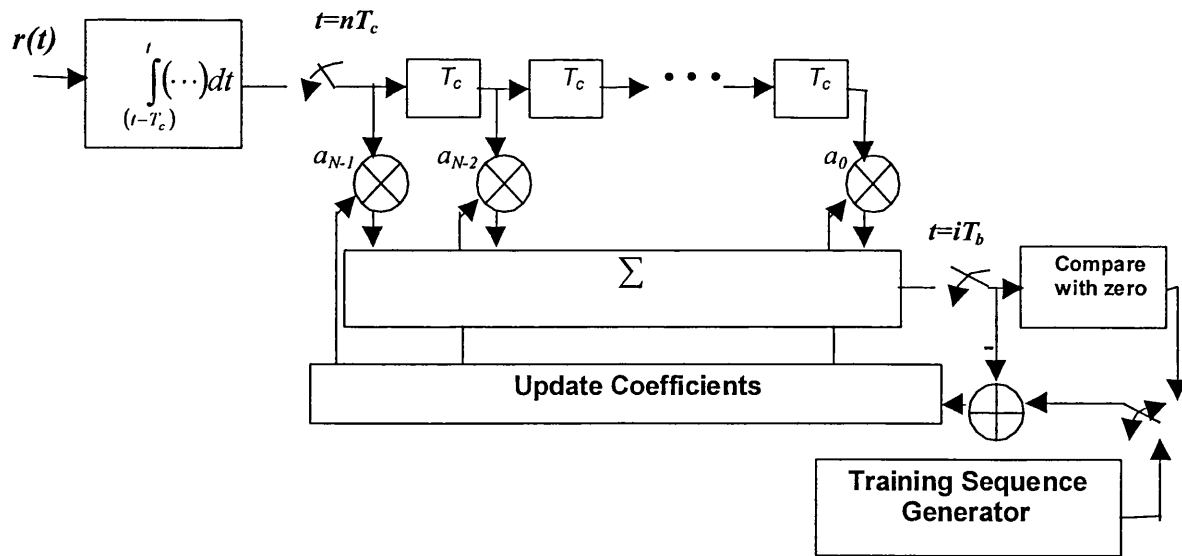
Figure 3. 3: The structure of the adaptive MMSE receiver.

An adaptive algorithm like the least mean square (LMS) is used to update the adaptive filter's weights, which is chosen to minimise the mean-squared error.

$$E[|e(i)|^2] = E[|b_1(i) - W^H(i)r(i)|^2]$$

(3-39)

In equation (3-39), $W(i)$ is the weights vector and is well-known to be [3- 13]:

$$W(i) = R^{-1}(i)P(i)$$

(3-40)

where $R(i) = E[r(i) \ r^H(i)]$ and $P(i) = E[b_1(i)r(i)]$ are the auto-correlation matrix and steering vector, respectively.

The data bit is detected by correlating the received vector with a complex weight vector, which is chosen via an adaptive algorithm to minimise the mean-square error.

$$\hat{b}_1(i) = \text{sgn}\{ \text{Re}[W^H(i)r(i)] \}$$

(3-41)

In the case of the line-of-sight transmission and a single-user environment, according to the equation (3-30), the auto-correlation matrix, the steering and the weighting vectors can be calculated as below:

$$R(i)=|A|^2 \ c_1 c_1^H + 2\sigma^2 I, P(i) = Ac_1, \ W(i) = \frac{Ac_1}{|A|^2 \ N + 2\sigma^2} \tag{3-42}$$

In equation **(3-42)**, σ^2 is the variance of the noise vector N_i. As can be seen, the weight vector is proportional to the signature waveform of the desired user and this leads to the conventional matched filter receiver that is optimum maximum-likelihood solution in this case. As has been shown in several papers, such as [3- 5], in a 'Near-Far' multiple-access environment, the performance of the adaptive MMSE receiver is far better than the performance of the conventional matched filter receiver. In this case, the adaptive MMSE receiver has good performance in combating the effect of MAI in the multiple-access DS-CDMA environments.

In a static multipath environment, the ability of the adaptive MMSE receiver to collect different rays of propagated energy in the channel, as for the RAKE receiver is excellent. In this case, according to the received signal vector in equation **(3-33)**, the auto-correlation matrix, the steering and the weighting vectors are as below:

$$R(i)=\sum_{m=1}^{P}[(a_m^1)^2 c_{1,m} c_{1,m}^H + 2\sigma^2 I], \ P(i)=\sum_{m=1}^{P} a_m^1 e^{j\varphi_m^1} c_{1,m}, \ W(i)=\frac{\sum_{m=1}^{P} a_m^1 e^{j\varphi_m^1} c_{1,m}}{\sum_{m=1}^{P}[(a_m^1)^2 N + 2\sigma^2]}$$

$$\tag{3-43}$$

As can be seen, the weight vector of the adaptive MMSE receiver is proportional to the impulse response of the multipath channel, which is needed to implement the RAKE combiner. This result leads to a receiver that performs like the RAKE receiver, which has the optimum performance in this case. In a multiple-access environment with 'Near-Far' effect, the strong MAI degrades the performance of the RAKE receiver. In this case, the adaptive nature of the MMSE receiver combats the effect of multipath channel and rejects the MAI. As it will be shown in chapter six, the performance of the adaptive MMSE receiver is much better than the RAKE receiver and it has a good performance to combat the effect of MAI in the multiple-access and multipath DS-CDMA environments.

To investigate the behaviour of the adaptive MMSE receiver in the fading channels, it is necessary to start with a flat fading environment. In this case, the line-of-sight transmitted signal is passed through a time varying channel, where its amplitude and phase are changed by the fading process. In a single-user case, the received vector, which is shown in equation **(3-35)**,

has time varying amplitude and phase that indicate the fading process. In a very slow rate fading, where the parameters of the fading remain constant over many bit intervals, the adaptive algorithm can track these constant parameters. However, for the case of fast rate fading, the adaptive algorithm, which adjusts the weight vector, can only track the mean value of the fading process and in this situation, it is found that [3- 19]:

$$R(i) = c_1 c_1^H + 2\sigma^2 I, \quad P(i) = A_1 e^{j\phi_1} c_1, \quad W(i) = \frac{A_1 e^{j\phi_1} c_1}{N + 2\sigma^2} \tag{3-44}$$

In equation (3-44), $A_1 e^{j\phi_1}$ is the mean value of the complex flat fading process. It is noted that, if the fading is a process with Rayleigh distribution, $A_1 = 0$ and hence, $W(i) = 0$ and the adaptive MMSE receiver can not combat the effect of fast rate Rayleigh-fading environment. As can be seen, the adaptive MMSE receiver does not take into account the phase variation of the channel and hence $W(i)$ is no longer matched to the desired user's signature waveform and hence the performance degradation will occur.

In a multi-user environment, because of presence the other co-channel users' signals, the performance degradation will be more than the single-user situation. In this case, the desired user's signal is affected by the other co-channel users' signals, which have been changed by independent fading processes. These problems make the standard form of the adaptive MMSE receiver useless in a Rayleigh-fading channel. In the multipath-fading channel, this problem will be continued and it is needed to make a modification to the structure of the adaptive MMSE receiver. In the next section, a modification to the standard form of the MMSE structure is presented, which allows the receiver to function in a multipath-fading channel. This structure uses a separate channel's impulse response tracking and estimating mechanism to relieve the adaptive filter from the responsibility of tracking channel impulse response variations.

3.5 The Modified Adaptive MMSE Receiver

As has been noted in section **3.4**, the performance of the adaptive MMSE receiver in a multipath-fading channel depends on the rate of the fading process. If the parameters of fading remain constant over many bit intervals, the adaptive algorithm can track these slowly varying parameters. However, in the case of fast fading, the adaptive algorithm, which adjusts the weight vector, can only track the mean value of the fading process. The main problem with an adaptive implementation of the MMSE receiver seems to be that the adaptive filter loses phase lock on the desired user during deep fades in the fast fading channels. In this situation, there are benefits in tracking and estimating the channel impulse response and using it in a channel equaliser to relieve the adaptive MMSE receiver to function in the multipath-fading channel. The main duty of this equaliser is to track the channel impulse response and remove the phase variation from the received signal before it enters into the adaptive filter. Then the MMSE structure should perform better in a Rayleigh fading channel.

Given an estimate of the desired user's channel impulse response, $h_d(\tau;t)$, the amplitude and phase variation are removed from the desired portion of the received signal by forming:

$$r_e(t) = r(t) * h^*_d(\tau;t) \tag{3-45}$$

In equation (3-45), $h^*_d(\tau;t)$, is the complex conjugate of the desired user's multipath-fading channel impulse response, $r(t)$ is the received signal, and $r_e(t)$ is the equalised version of the received signal. If the channel estimation is a good approximation to the actual impulse response, then the adaptive filter does not require to make any attempt to track the channel variations. If the estimated impulse response is good, the output of the equalising filter should consist of the desired signal, noise, and a small amount of the multiple-access interference. However in a multiple-access environment with 'Near-Far' effect, the error of the estimation process increases. In this situation the adaptive nature of filter could be helpful.

In the flat fading channel, a mechanism is needed to track the channel phase and remove the phase variation from the received signal before it enters to the adaptive filter. In this situation, the equalised version of the received i^{th} samples is as below:

$$r_e(i) = e^{-j\hat{\phi}_1(i)} r(i) \tag{3-46}$$

In equation **(3-46)**, $\hat{\varphi}_1^1(i)$ is the estimated channel phase of the desired user in the ith bit duration. By using $r_e(i)$, the adaptive filter makes a decision on $b_1(i)$. A technique for estimating the phase of channel is to use a linear predictor, which employs coefficients, α_m, that are chosen to minimise the mean square error of prediction [3- 11].

$$\hat{\beta}_1^1(i) = \sum_{m=1}^{L} \alpha_m \beta_1^1(i-m) \qquad (3\text{-}47)$$

In equation **(3-47)**, $\hat{\beta}_1^1(i)$ is the Lth order linear prediction and $\beta_1^1(i)$ is the noisy version of the channel amplitude and phase fading process during the ith bit interval. The noisy measurement of the channel fading process during the ith bit interval for the desired user can be calculated as:

$$\beta(i) = b_1(i) W^H(i) r(i) \qquad (3\text{-}48)$$

where $b_1(i)$ is the known data bit during training mode or the detected data bit in decision-directed mode. The phase estimate is found by $\hat{\varphi}_1^1(i) = \angle\hat{\beta}_1^1(i)$. In this technique the coefficients, α_m, are chosen to minimise the mean square error $E[|a_1^1(t)e^{j\varphi_1^1(t)} - \hat{\beta}_1^1(i)|^2]$. It is found that using this technique in a fast flat fading multi-user channel, improves the BER performance of the adaptive MMSE receiver and enables it to combat the effect of fading channel [3- 19].

To extend the above modification to the adaptive MMSE receiver so that it can function in the multipath-fading channel, it is necessary to use a technique to estimate the impulse response of the multipath channel. One possible method is to estimate the channel's impulse response from the cross-correlation between the received signal and the signature waveform of the desired user. This method of estimating the channel impulse response is not perfect because the length of the signature waveform is limited and the processing gain is not infinite and hence the auto-correlation of the signature waveforms is not a pure delta function. In addition, the MAI and AWGN introduced by the channel decrease the accuracy of the estimation. A better technique is to use maximum-ratio combining (MRC), which can be used with a simple alpha tracker [3- 18] for estimating the multipath channel impulse response. This algorithm requires a short time window to form an estimate and has low complexity. Separate alpha trackers are employed to estimate the in-phase and quadrature components of the channel impulse response:

$$h_j(i)_I = (1-\alpha) \cdot b_1(i-1) \cdot x_j(i-1)_I + \alpha \cdot h_j(i-1)_I$$
$$h_j(i)_Q = (1-\alpha) \cdot b_1(i-1) \cdot x_j(i-1)_Q + \alpha \cdot h_j(i-1)_Q$$

(3-49)

In equation (3-49), $x_j(i)$ and $h_j(i)$ are the jth post-correlation received ($j=0,...,N$-1) sample and the estimated channel coefficient in the ith bit duration respectively, $b_1(i$-1) is the previous decided bit and α is a constant parameter, $0<\alpha<1$, that is set to have higher performance. As can be seen, this technique uses the previous detected bit to estimate the channel characteristic at present and hence the channel estimates obtained from this technique will be at the bit rate. It is shown in [3- 18], that this technique has a good performance to estimate the multipath channel impulse response in a single-user fast rate Rayleigh-fading DS-CDMA environment. By using the channel equaliser, the input signal to the adaptive part of the receiver contains the desired signal, noise and the MAI. In this situation, the adaptive nature of the MMSE receiver can reject the MAI and detect the desired user's signal properly.

The structure of the modified MMSE receiver, which uses the MRC technique to estimate the delay profile and attenuation coefficients of the multipath channel, is shown in Figure 3. 4. The complex conjugate of the estimated parameters is used to equalise and remove the multipath channel's effect on the desired user's received signal before it enters into the adaptive transversal filter. In this case, the adaptive part of the MMSE receiver is able to function better as a MAI rejecter in the Rayleigh fading-multipath channel.

The performance of the modified adaptive MMSE receiver in different conditions of the multiple-access and multipath-fading DS-CDMA environment will be evaluated in chapter six.
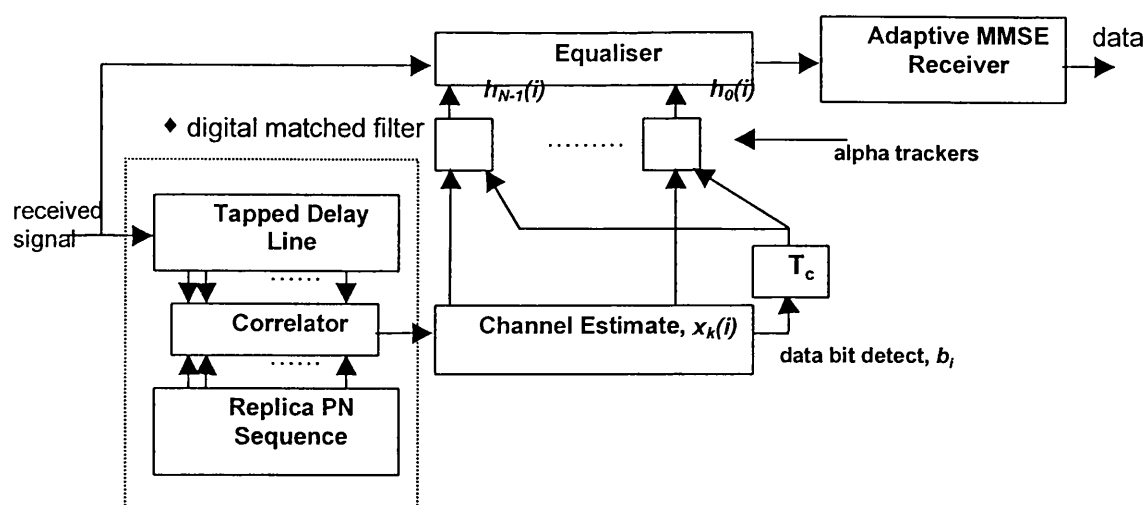
Figure 3. 4: The structure of the modified adaptive MMSE receiver.

3.6 Summary

In this chapter the adaptive MMSE receiver in a DS-CDMA environment has been considered. It is shown that this receiver, with a low implementation complexity, can be used as a DS-CDMA receiver and it has good performance in the different scenarios of channel model. In this case, the adaptive MMSE receiver is able to despread the desired user's signal, reject the MAI, and combat the effect of multipath-fading channel.

In an AWGN single-user DS-CDMA channel, where the conventional matched filter receiver has the best performance, the adaptive MMSE receiver does not require any additional information and with a short period of training, its performance is identical as the conventional matched filter receiver. In the static multipath single-user channel, where the RAKE receiver is used as the best receiver to collect the distributed energy of transmitted signal in the multipath channel, the performance of the adaptive MMSE receiver is found to be identical as the RAKE receiver. In the multi-user environment, where the conventional matched filter and the RAKE receivers lose their ability to receiver the desired user's signal, the adaptive MMSE receiver has a good performance to detect the desired user's signal. In this case, this receiver as a MAI rejection receiver rejects the co-channel other user's signals in the multiple-access DS-CDMA environment. To function in the fast varying mobile channel, the structure of the adaptive MMSE receiver has been modified. The new proposed modification consists of a channel estimator to help the adaptive part of receiver to follow and estimate the rapid time varying

parameters of the channel. The new modified adaptive MMSE receiver is able to detect the desired user's signal in the multi-user and multipath fading DS-CDMA environment.

The performance of the adaptive MMSE receiver will be evaluated via Monte Carlo simulation in the chapter six. The low complexity and good performance of the adaptive MMSE receiver makes it attractive for use in the both base-station and mobile handset in the future mobile systems.

3.7 References

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Chapter Four

Artificial Neural Network Receivers in DS-CDMA System

4.1 Introduction

After recognising that the brain computes in a different way from the conventional digital computers, work on the 'neural network' has been started. Neural computing is a rapidly expanding branch of computing whose origins date back to the early 1940s. It has been largely overshadowed since the 1960s by the conventional computing, but had an upgrade in acceptance in the late 1980s. This was a result of the discovery of new techniques and developments and general advances in the computer hardware technology. Neural networks find more and more applications in many engineering areas ranging from the optimisation of the spatial distribution of transmitters in the cellular telephony systems to the identification of the parameters of very complex industrial processes [4- 1].

The brain is a highly complex, non-linear, and parallel information processing system. It has the capability to perform certain computations such as pattern recognition, many times faster than the fastest digital computer in existence today. In the most general form, a neural network is a machine that is designed to model the way in which the brain performs a particular task or function of interest. The user allows the neural network to adapt itself during a training period, based on the examples of similar problems often with a desired solution to each problem. After sufficient training, the neural network is able to relate the problem data to the solutions, inputs to outputs, and it is then able to offer a good solution to a new problem.

Work on artificial neural networks started in 1943 when McCulloch and Pitts [4-2] introduced a simple model which summed its inputs and generated an output if a certain threshold was achieved. Then in 1962, using the McCulloch and Pitts' model, Rosenblatt [4- 3] developed a system that could be trained to recognise simple patterns. This system became known as a 'perceptron'. Later, the interest in the neural networks fell off and the conventional computing overshadowed it. After twenty years continuous development in computer hardware technology, neural networks became practical proposition and found a number of applications in many areas. In 1982, Hopfield [4-4] used the idea of an energy function to formulate a new way of understanding the computation performed by the recurrent neural networks and this particular class of the neural network with feedback attracted a great deal of attention. In 1986, Rumelhart, Hinton and Williams [4-5] reported the development of the back-propagation algorithm that is a famous training algorithm. In 1988, Broomhead and Lowe [4-6] described a procedure for the design of layered feedforward networks using the radial basis functions.

The first paper that considered the application of adaptive neural network receivers to multi-user detection is due to Aazhang, Paris and Orsak [4-7]. They studied a multi-layer perceptron structure as a receiver in a DS-CDMA environment. Each node in the first stage computes a non-linear function of a linear mapping of the matched filter outputs. The signature waveforms are assumed to be known in advance and training sequences are used in order to adapt the linear mapping of the matched filter outputs. Assuming knowledge of the desired user's spreading code, Mitra and Poor [4-8] proposed a single-layer perceptron model and used a non-linear function as an update term for the adaptive linear mapping. A radial basis function neural network was proposed in [4-9] for single-user detection and has been investigated in [4-10] for synchronous multi-users detection. Miyajima, Hasegawa and Haneishi [4-11] proposed a recurrent neural network for the synchronous multi-users detection using a likelihood function as the energy function to be minimised. The weights of the network are not adaptive and equal to the cross-correlation of the signature waveforms. Hottinen [4-12] has examined the application of the self-organising map to the synchronous multi-users detection. This algorithm works with a matched filter bank front-end, and hence it assumes knowledge of the signature waveforms of all users.

This chapter contains a brief description of the neural network concept and its application to DS-CDMA communication systems. A definition of the neural network is provided in the following section and the benefits of the neural network in offering solutions to different problems will be reviewed. In the third and fourth sections of this chapter, the model of a neuron with different activation functions and its main structure for implementing the neural network will be explained. Learning algorithms is the subject of the fifth section and different training algorithms related to training the neural network will be explained. In the sixth section, the dynamical considerations of the recurrent neural network are considered. Using the multi-layer perceptron neural network as a DS-CDMA receiver is the subject of the seventh section. The use of adaptive MLP neural networks as single-user and multi-user receivers are then considered. The eighth section contains an investigation into the use of the recurrent neural network structure as a DS-CDMA multi-user receiver and a summary of the chapter comes in the final section.

4.2 Definition and Benefits of Artificial Neural Networks

The topology of an artificial neural network contains a large number of interconnected simple computing cells referred to as 'neurons' or 'processing units'. In most common networks, neurons are arranged in layers with the input data fed to the network at the input layer. The data

then passes through the network to the output layer to provide the solution or answer. The network is usually implemented using electronic components or simulated in software on a digital computer.

A general definition of an artificial neural network as an adaptive machine is as below [4-13]:

'An artificial neural network is a parallel-distributed processor that has a natural property for storing experiential knowledge and making it available for use. It matches the brain in two features:

    1. Knowledge is acquired through a learning process by the network.

    2. Inter-neuron connection weights are used to store the knowledge.'

From the above definition, it can be seen that the neural network derives its computing power through a large parallel-distributed computing structure and its ability to learn and, therefore, generalise. These two information-processing capabilities enable neural networks to solve the complex problems. The use of neural network offers the following benefits and capabilities:

♦ *Nonlinearity*: A neuron is a non-linear cell and the neural networks that are made up of layers of neurons are also non-linear. This property of neural network is very important and enables it to solve realistic non-linear problems.

♦ *Input-Output Mapping:* One of the most important properties of the neural network is its ability to map input patterns to the desired outputs. During the learning mode, by applying the test patterns and the desired outputs, a suitable algorithm changes the values of the interconnection weights in the neural network structure. The training of the network is repeated for many examples until the network reaches a steady state, where there are no further significant changes in interconnection weights. In this situation, the network has learned to construct an input-output mapping for the desired problem.

♦ *Adaptivity:* The various structures of neural networks have the capability to adapt their interconnection weights with changes in the surrounding environment. This property helps the neural network to correct its behaviour when subject to new input conditions. Moreover, when it is operating in a nonstationary environment, whose statistics change with time, a neural network can be designed to change its weights in the real time.

♦ *Ability to deal with new kinds of problems:* Neural computers are effective at solving problems whose solutions are difficult. This can involve a new range of applications that formerly was difficult or impossible to computerise.

♦ *Robustness:* Neural networks are more robust than conventional solution methods. They have the ability to cope well with incomplete data or previously unspecified situations. By using distributed processing rather than the centralised architecture of conventional computing methods, this protects the neural network from failure if properly implemented.

♦ *Fast processing speed:* Neural networks consist of a large number of interconnected processing units, all operating in parallel on the same problem. For this reason they can operate at considerable speed.

♦ *Flexibility and ease of maintenance:* Neural computers are very flexible in the way in which they are able to adapt their behaviour to new and changing environments. They have the ability to learn from experience in order to improve their own performance.

♦ *VLSI Implementability:* The parallel nature of the neural network and the fact that each neuron is identical in structure makes neural networks ideal for implementation using very large scale integrated (VLSI) technology. Using this technology makes it possible to employ the neural network processors in the real time applications such as signal processing [4- 1].

4.3   Different Models of a Neuron or Processing Unit

A neuron is an information-processing unit that is the fundamental part of a neural network. Within the network each neuron is usually a simple processing unit that takes one or more inputs and produces an output. Each neuron has three basic elements, which are shown in Figure 4. 1. The first is a set of connection links, which are characterised by weights. For example each input signal to the kth neuron, x_j, is multiplied by a weight, w_{kj}. The first subscript in w_{kj} refers the neuron and the second subscript shows the input signal.
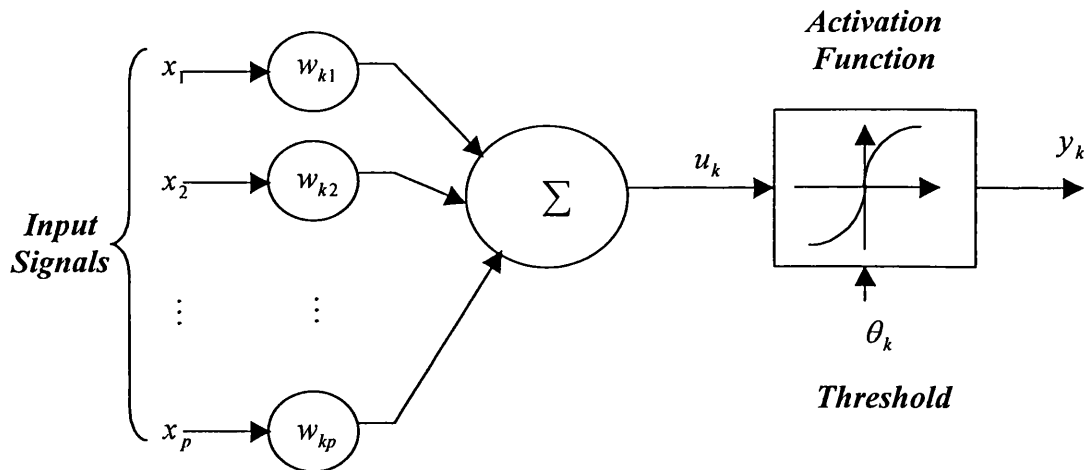
Figure 4. 1: Non-linear model of a neuron.

The second element in the structure of the neuron is a linear combiner, which sums the weighted inputs to form u_k. The third and the last element in the model of a neuron is an activation function, $\varphi(.)$, which acts as a limiter to shape the output signal of neuron. The limitation range is usually [0,1] or [-1,1]. In Figure 4. 1, the non-linear model of a neuron also includes a threshold θ_k, which is an applied signal external to the neuron which controls the non-linearity of the activation function.

The relationship between inputs and output in the model of a neuron can be written as below:

$$u_k = \sum_{j=1}^{p} w_{kj} x_j$$
(4-1a)

$$y_k = \varphi(u_k - \theta_k)$$
(4-2b)

In equations **(4-1a)** and **(4-1b)**, $x_1, \cdots, x_p$ are the input signals; $w_{k1}, \cdots, w_{kp}$ are the weights of the kth neuron; u_k is the linear combiner output; θ_k is the threshold; $\varphi(\cdot)$ is the activation function and y_k is the output signal of the neuron. The threshold θ_k is an external parameter of the neuron k. By defining $v_k = u_k - \theta_k$, equations **(4-1a)** and **(4-1b)** can be rewritten as below:

$$v_k = \sum_{j=0}^{p} w_{kj} x_j$$
(4-2a)

$$y_k = \varphi(v_k)$$ (4-2b)

In equations **(4-2a)** and **(4-2b)**, it will be seen that instead of the threshold θ_k, a new input link with an input value of $x_0 = -1$ and a weight of $w_{k0} = \theta_k$ can be added to the model of the neuron. Figure 4. 2 shows another non-linear model of a neuron based on the equation **(4-2)**.
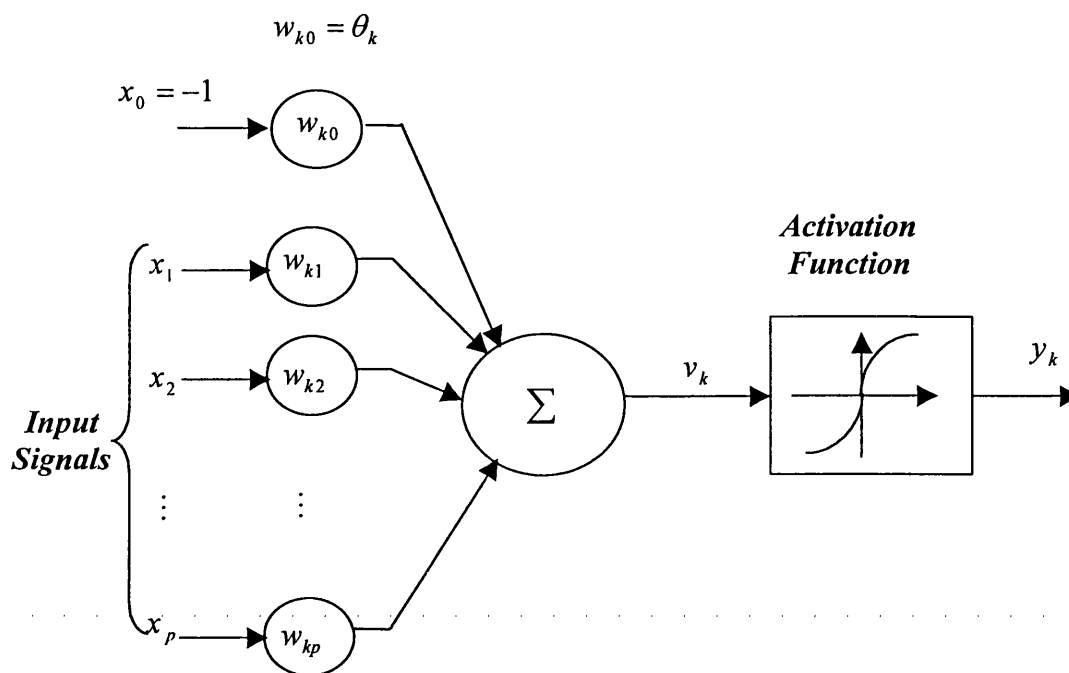
Figure 4. 2: Another non-linear model of a neuron.

4.3.1 Different Types of Activation Functions

The ability of artificial neural networks to solve realistic non-linear problems is determined by the internal structure and interconnection of neurons (e.g. how many neurones and how many layers). The activation function used is one of the most important parts of the structure of a neuron. The suitable choice of the activation function plays an important role in the behaviour of the network. In general, the activation functions can be divided into three types as below:

1. **Threshold Function**: The threshold function is the simplest type of activation function, which has two levels at the output according to the value of the input signal. The relationship between the input and the output of this activation function is:

$$\varphi(v) = \begin{cases} 1 & \text{if} \quad v \geq 0 \\ 0 & \text{if} \quad v \prec 0 \end{cases}$$ (4-3)

In this model, the output of the neuron, takes either a '0' or '1' output depending on the sign of the input signal.

2. Piecewise-Linear Function: The piecewise-linear function is the second type of activation function, which has a linear part between two saturated regions of its characteristic function. Equation (4-4) describes the input-output relationship and Figure 4. 3 describes this type of activation function.

$$\varphi(v) = \begin{cases} 0 & \text{if} \quad v \leq -\dfrac{1}{2} \\ v + \dfrac{1}{2} & \text{if} \quad -\dfrac{1}{2} \prec v \prec \dfrac{1}{2} \\ 1 & \text{if} \quad v \geq \dfrac{1}{2} \end{cases}$$ (4-4)
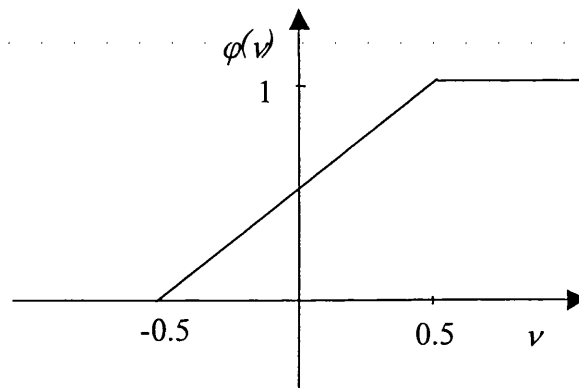
Figure 4. 3: The characteristic of the piecewise-linear activation function.

3. Sigmoid Function: The sigmoid function is the most common activation function that is used in the neural network structures. An example of this activation function is 'logistic function', defined as:

$$\varphi(v) = \frac{1}{1 + \exp(-bv)}$$ (4-5)

In equation **(4-5)**, *b* is the slope parameter that changes the slope of the sigmoid function's curve. Figure 4. 4 shows the characteristic diagram of a typical 'logistic function'.
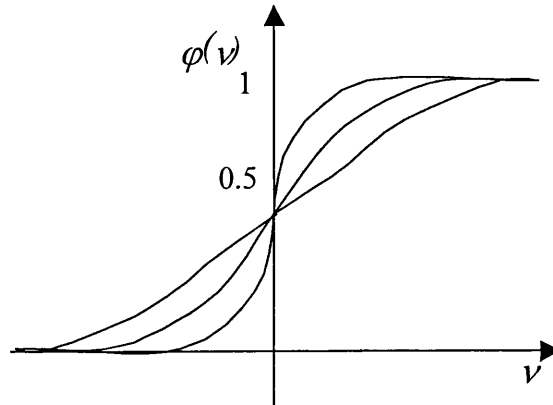
Figure 4. 4: The characteristic diagram of the logistic activation function.

As can be seen, the parameter *b* controls the slope of characteristic diagram. In the limit, as the slope parameter approaches to infinity, the sigmoid function becomes a threshold function.

The range of activation functions defined by equations **(4-3)**, **(4-4)** and **(4-5)** is from '0' to '1'. It is sometimes desirable to have an activation function range from '-1' to '1'. In this situation, the activation functions will be symmetrical with respect to the origin. According to the new range, the threshold function in the equation **(4-3)** is redefined as:

$$\varphi(v) = \begin{cases} -1 & if & v \prec 0 \\ 0 & if & v = 0 \\ 1 & if & v \succ 0 \end{cases}$$

(4-6)

For the sigmoid function, the new function becomes the 'hyperbolic tangent function', which has a symmetrical form with respect to the origin, defined as:

$$\varphi(v) = \tanh(v) = \frac{1 - \exp(-bv)}{1 + \exp(-bv)}$$

(4-7)

In this case, *b* is the slope of characteristic diagram, as before. The 'hyperbolic tangent function' is the most popular activation function in most applications of the neural network.

4.4 The Structure of Artificial Neural Networks

The interconnection of neurons in the structure of an artificial neural network generates several different types of networks. From the viewpoint of the application, the required structure of a neural network is very important if a solution is to be obtained. In general, there are four different classes of network structure that have been developed so far. These are the single-layer perceptron, the multi-layer perceptron, the recurrent and the lattice neural network.

4.4.1 Single-Layer Perceptron Neural Networks

A layered neural network is a network of neurons organised in the form of layers. The simplest layer structure is a single-layer perceptron that contains an input layer of source nodes and an output layer of neurons or computation nodes. In this network all of the paths are feedforward and there is no feedback between the outputs and inputs of the network. The information obtained via the training algorithm when the network is in the learning mode is stored in the interconnection weights. Figure 4. 5 shows the structure of a single-layer perceptron neural network.

Input   Output
Layer   Layer
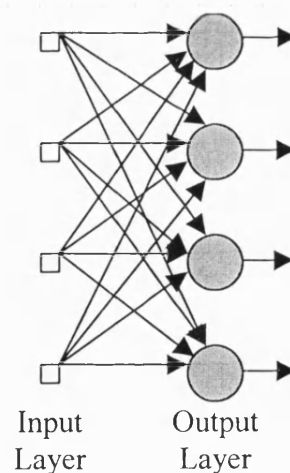
Figure 4. 5: The structure of a single-layer perceptron neural network.

4.4.2 Multi-Layer Perceptron (MLP) Neural Networks

The multi-layer perceptron network is one of the most popular and successful neural network topologies, which is suited to a wide range of applications. These applications consist of pattern

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discrimination and classification, pattern recognition, interpolation, prediction and process modelling. The multi-layer perceptron network is achieved by adding one or two hidden layers to the structure of the single-layer perceptron. The hidden layers are placed between the input and output layers. These hidden layers enable the neural network to perform higher complexity tasks. Figure 4. 6 (a) shows the structure of a typical multi-layer perceptron that contains layers with 4 input nodes, 4 hidden nodes and 2 output nodes. As can be seen, all of the input nodes are connected to the hidden nodes and all outputs of the hidden nodes are connected to the output nodes in the network. This network is known as a fully connected MLP neural network. The partially connected neural network is another multi-layer neural network structure. In this structure, some of the interconnections in several parts of the network are missed and when compared with the fully connected MLP neural network, it has fewer weights in its structure. Figure 4. 6 (b) shows the structure of a typical partially connected multi-layer perceptron neural network.

| Input | Hidden | Output | Input | Hidden | Output |
| Layer | Layer | Layer | Layer | Layer | Layer |

(a)   **(b)**
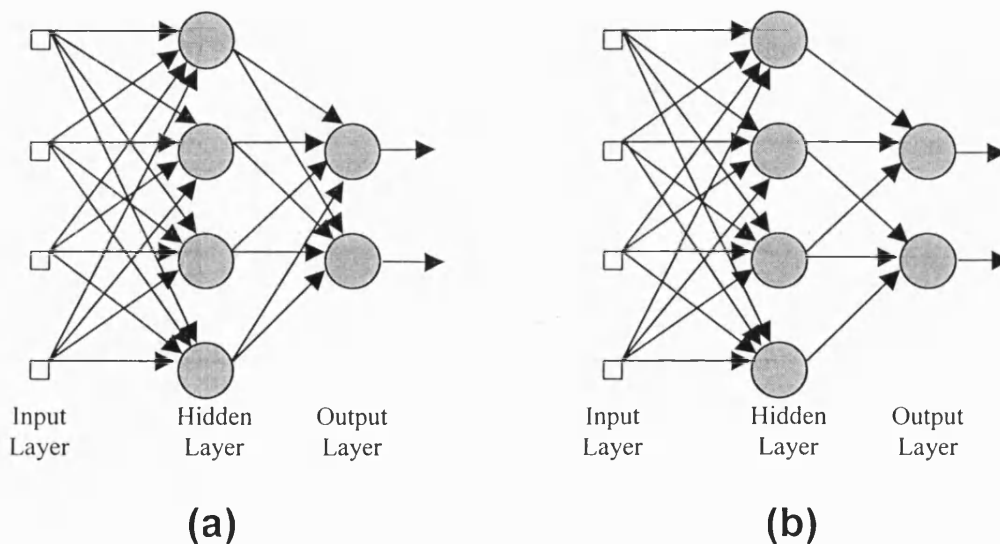
Figure 4. 6: The structure of a typical fully connected (a) and partially connected (b) multi-layer perceptron neural network.

Typically, a multi-layer perceptron is employed to classify patterns based on the input vectors presented to the network, for example a multi-layer perceptron network with 'N' outputs can discriminate between 'N' input patterns. In this situation the network is trained such that a '1' appears on a particular output and other outputs remain '0'.

As reported in the various studies of multi-layer perceptrons [4-14], determining the number of nodes in the hidden layer sufficient for a given task, is an open problem and depends on the nature of pattern classification tasks.

4.4.3 Recurrent Neural Network

The recurrent neural network is another type of neural network topology which includes at least one feedback loop in its structure. The presence of feedback loops in the structure of the recurrent neural network distinguishes it from feedforward neural networks. For example, a recurrent neural network may consists of a single layer of neurons in which the output of each neuron is fed back to the inputs of all other neurons via unit delay elements. Input signals can be entered via neurons to the network and in this situation the network will be able to map input patterns to the desired outputs. Figure 4. 7 shows the structure of a recurrent neural network, in which **D** is a symbol that shows the unit delay in the feedback path. It should be noted that there are not any self-feedback loops in the structure of the recurrent neural network.
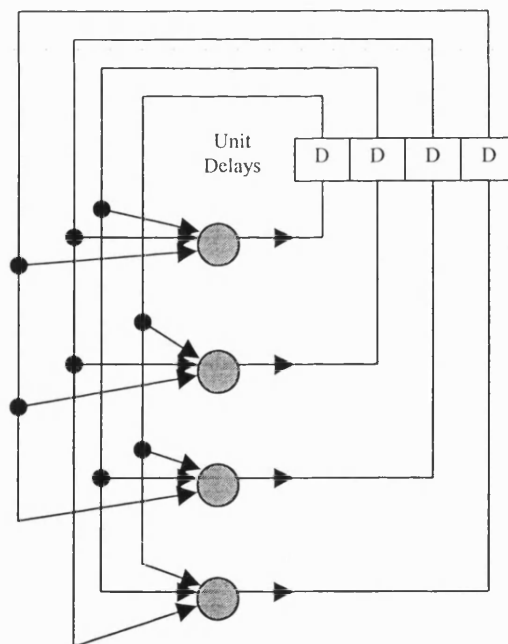
Figure 4. 7: The structure of a recurrent neural network.

Because of the feedback, recurrent neural networks are able to store time changing information and therefore they are suitable for predicting several types of time series data. It will be shown that the recurrent neural network has the potential to be used for implementing the multi-user receiver in the multiple-access DS-CDMA environments.

4.4.4 Lattice Structure Neural Network

A lattice structure neural network consists of an array of neurons and sources which input signals to the array. Figure 4. 8 shows the structure of a typical lattice neural network, which is really a feedforward network.

Input
Layer
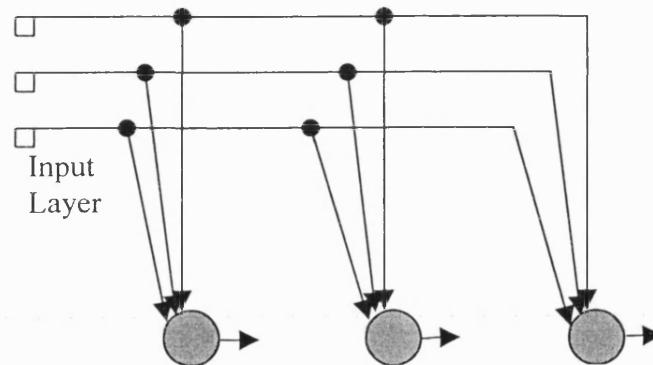
Figure 4. 8: The structure of a typical lattice neural network.

There are several types of the neural network architectures which are employed for different applications in special areas. For example the radial basis functions network, the learning vector quantisation network, the auto-associative neural network and the self-organising maps are some types of the neural network structures that have been examined for different applications [4-13]. As it has been said, the multi-layer perceptron structure is the most popular and successful neural network topology, which is used, in a wide range of applications. These applications consist of pattern discrimination and classification that is useful to be implemented as a DS-CDMA receiver. Also the recurrent neural network receiver has suitable feature to be employed for implementing the multi-user receiver in this field.

4.5 Learning Algorithms

One of the most interesting properties of the neural networks is its ability to learn from its environment and to improve its performance through learning. A neural network learns about its environment through an iterative process of adjustments applied to its interconnection weights and thresholds. Ideally, after each iteration of the learning process, the knowledge of the neural network about its environment is increased.

There are many types of learning algorithm which can be used to train a neural network. One of the most powerful training methods is supervised training, which works in the same way as a human learns new skills, by showing the network a series of examples. The most common supervised training algorithm, which is particularly well suited to the feedforward neural network, is known as the 'back-propagation' algorithm.

Figure 4. 9 shows the signal flow graph of a neuron. In this graph, $w_{kj}(n)$ denote the value of interconnection weight w_{kj} at time n. At this time, an adjustment $\Delta w_{kj}(n)$ is applied to the $w_{kj}(n)$ and the updated value $w_{kj}(n+1)$ at time $n+1$ will be as below:

$$w_{kj}(n+1) = w_{kj}(n) + \Delta w_{kj}(n) \qquad\qquad (4\text{-}8)$$

In equation **(4-8)**, $w_{kj}(n)$ and $w_{kj}(n+1)$ are the old and the new values of the interconnection weight w_{kj}. As it is known, there is no unique learning algorithm for neural networks. Basically, learning algorithms differ from each other in the way in which the adjustment $\Delta w_{kj}(n)$ is formulated.
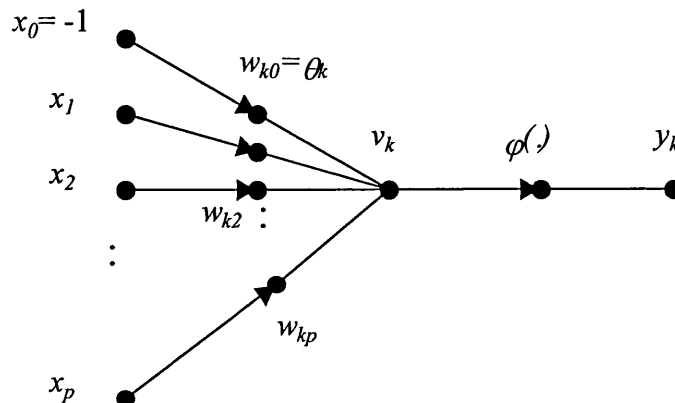
Figure 4. 9: Signal flow graph of a neuron.

4.5.1 The Error Correction Learning Algorithm [4-13]

Error correction learning is the simplest learning algorithm to adjust the interconnection weights and the threshold levels for a single-layer perceptron neural network. During the training mode, the weights of the interconnection and thresholds are changed so the minimum mean square error between the desired and the real output signals of the network is minimised. This technique is a well-known method in the adaptive systems.

Let $d_k(n)$ and y_k (n) denote the desired and the actual responses for neuron k at time n. Typically, the actual response of neuron k is different from the desired response and the error signal $e_k(n)$, can be defined as the difference between the desired and the actual responses of neuron.

$$e_k(n) = d_k(n) - y_k(n) \qquad (4\text{-}9)$$

The mean square error J, is defined as the mean square value of the sum of squared errors:

$$J = E\left[\frac{1}{2}\sum_k e_k^2(n)\right] \qquad (4\text{-}10)$$

In equation **(4-10)**, E is the statistical expectation operator and the summation is over all the neurons in the output layer. The factor ½ is used for simplifying to derive results from the minimising J. Minimising J with respect to the network parameter leads to the well-known gradient descent algorithm [4- 15]. However, there is not any information about the statistical characteristic of the process, an approximate solution to the optimising problem can be accessed by using $\varepsilon(n)$, the instantaneous value of the sum of squared errors as the criterion of interest.

$$\varepsilon(n) = \frac{1}{2}\sum_k e_k^2(n) \qquad (4\text{-}11)$$

According to the error correction learning rule, the adjustment $\Delta w_{kj}(n)$ made to the interconnection weight w_{kj} at time n is given by [4- 16]:

$$\Delta w_{kj}(n) = \alpha \, [d_k(n) - y_k(n)] \, x_j(n) \qquad (4\text{-}12)$$

In equation **(4-12)**, α is a factor that shows the step-size and its value is less than 1, d_k *(n)* is the desired output of the kth output in the network, y_k *(n)* is the actual value of the kth output in the network and x_j *(n)* is the jth input signal. As can be seen, the weights are unchanged if the correct decision is made by network. This technique is very powerful for adjusting the interconnection weights and is implemented by initialising the interconnection weights and thresholds by small random values. By presenting the input pattern, the actual output of network can be calculated and used with the desired output to change the value of weights as equation **(4-12)**.

4.5.2 The Delta Rule Algorithm [4-13]

For sharp activation functions, such as 'threshold function' in equation **(4-3)**, the performance of the error correction learning technique is not good enough. In this situation, however the weights are not exactly adjusted but the adjustment factor $\Delta w_{kj}(n)$ is zero and the algorithm unable to change the value of interconnection weights to achieve the best result. One way to correct this effect is to use the activation input signal, $v_k(n)$, instead of the activation output signal, y_k *(n)*, in equation **(4-12)**. The learning algorithm based on the gradient descent with this type of node is known as the 'delta rule' algorithm. In this algorithm the adjustment factor, $\Delta w_{kj}(n)$, is as below:

$$\Delta\, w_{kj}(n) = \alpha\, [d_k(n) - v_k(n)]\, x_j(n) \tag{4-13}$$

In equation **(4-13)**, α is a factor that shows the step-size and its value is between zero and one, $d_k(n)$ is the desired value of the kth output in the network, v_k *(n)* is the value of the kth input to the kth activation function in the network and x_j *(n)* is the jth input signal. In this situation, the error never be exactly zero and so there will always be some updates to the weights. The term $\alpha[d_k(n) - v_k(n)]$ is sometimes known as δ *(n)*.

There are several discontinuities in the error function related to a few types of activation function. These discontinuities in error are the result of discontinuities in the output signals of activation function. In this situation, the output signal of the neuron is used instead of the input signal of the activation function and an extra term, which is related to the slope of the sigmoid function, is included to the adjustment factor $\Delta w_{kj}(n)$.

$$\Delta w_{kj}(n) = \alpha\, \varphi'\, (v)\, [d_k(n) - y_k(n)]\, x_j(n) \tag{4-14}$$

In equation **(4-14)**, $\varphi'(v)$ is the derivative of activation function. For 'logistic function', which is defined in equation **(4-5)** with $b=1$, this term will be as below:

$$\varphi'(v) = \varphi(v)\ (1-\varphi(v)) \qquad\qquad (4\text{-}15)$$

For 'hyperbolic tangent function', which is defined in equation **(4-7)** with $b=1$, this term will be as below:

$$\varphi'(v) = (1-\varphi(v))^2 \qquad\qquad (4\text{-}16)$$

Unlike the error correction learning, the delta rule has the potential to be generalised to train more than one layer neural network. It means that it is possible to calculate the slope of the error gradient at intermediate layers of the multi-layer neural network. This learning technique is called 'back-propagation' algorithm, which is the most common supervised training algorithm and is particularly well suited to the feedforward neural network.

4.5.3 The Back-Propagation Algorithm

Among the algorithms that are employed to perform supervised learning, the 'back-propagation' is the most successful algorithm. Also it has the most widely used for the design of multi-layer feedforward neural networks. 'Back-propagation' algorithm is a generalisation of the 'error correction' and 'delta-rule' algorithms for using in multi-layer neural networks. The input signals propagate through layers in the network and produce some responses at the output. The actual responses are compared with the desired responses for generating error signals. These error signals propagate backward through the network to adjust the free parameters to minimise the square sum of errors.

The 'back-propagation' learning algorithm can be implemented by a procedure as below:

♦ **Initialisation**: Set all of the interconnection weights and threshold levels to small random numbers that have a uniform distribution.

♦ **Presentations of training examples**: Present the network with a training example and perform the forward and backward computation.

◆ **Forward computation**: Let $x(n)$ and $d(n)$ denote the example input and the desired output vectors of the neural network. The input of activation function for the jth neuron in the layer l is:

$$v_j^{(l)}(n) = \sum_{i=0}^{p} w_{ji}^{(l)}(n) y_i^{(l-1)}(n) \qquad (4-17)$$

In equation **(4-17)**, $y_i^{(l-1)}(n)$ is the function signal of the ith neuron in the previous layer $l-1$ at iteration n and $w_{ji}^{(l)}(n)$ is the interconnection weight of the jth neuron in the layer l that is fed from neuron i in the layer $l-1$. For $i=0$, $y_0^{(l-1)}(n) = -1$ and $w_{j0}^{(l)}(n) = \theta_j^{(l)}(n)$, where $\theta_j^{(l)}(n)$ is the threshold applied to neuron j in the layer l. Assuming the use of a 'logistic' activation function for the sigmoidal non-linearity[1], the output of neuron j in the layer l and its derivative are as below:

$$y_j^{(l)}(n) = \frac{1}{1 + \exp\left(-v_j^{(l)}(n)\right)} \; , \; \frac{\partial y_j(n)}{\partial v_j(n)} = y_j(n)\left[1 - y_j(n)\right] \qquad (4-18)$$

If neuron j is in the first hidden layer (i.e., $l=1$), set:

$$y_j^{(0)}(n) = x_j(n) \qquad (4-19)$$

In equation **(4-19)**, $x_j(n)$ is the jth element of the input vector $x(n)$. If the neuron j is in the output layer (i.e., $l=L$), set:

$$y_j^{(L)}(n) = o_j(n) \qquad (4-20)$$

where $o_j(n)$ is the jth element of the output vector of network. Error can be computed as below:

$$e_j(n) = d_j(n) - o_j(n) \qquad (4-21)$$

In equation **(4-21)**, $d_j(n)$ is the jth element of the desired response vector $d(n)$.

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[1] For hyperbolic tangent activation function, the output of neuron and its derivative are as in equations (4-7) and (4-16).

♦ **Backward Computation**: Compute the local gradient δ's of the network by proceeding backward, layer by layer. For neuron j in the output layer L:

$$\delta_j^{(L)}(n) = e_j^{(L)}(n) o_j(n) \left[1 - o_j(n)\right] \tag{4-22}$$

For the neuron j in the hidden layer l:

$$\delta_j^{(l)}(n) = y_j^{(l)}(n) \left[1 - y_j^{(l)}(n)\right] \sum_k \delta_k^{(l+1)}(n) w_{kj}^{(l+1)}(n) \tag{4-23}$$

Hence, adjust the interconnection weights of the neural network in the layer l according to the back-propagation algorithm:

$$w_{ji}^{(l)}(n+1) = w_{ji}^{(l)}(n) + \alpha \delta_j^{(l)}(n) y_i^{(l-1)}(n) \tag{4-24}$$

In equation **(4-24)**, α is the learning rate or step-size parameter. The value of this parameter determines the convergence rate of the back-propagation algorithm. Figure 4. 10 shows the simulation result of a multi-layer feedforward neural network with 31 nodes in the input, 15 nodes in the hidden and one node in the output layers. As can be seen, by choosing the small value for the step-size parameter, sum square error requires more iteration to decrease to its minimum value. On the other hand, by increasing the value of step-size parameter, the speed of convergence is increased and after a few iterations, sum square error is decreased to an acceptable value. If the step-size parameter is chosen too large so as to speed up the rate of learning, the network may become unstable.
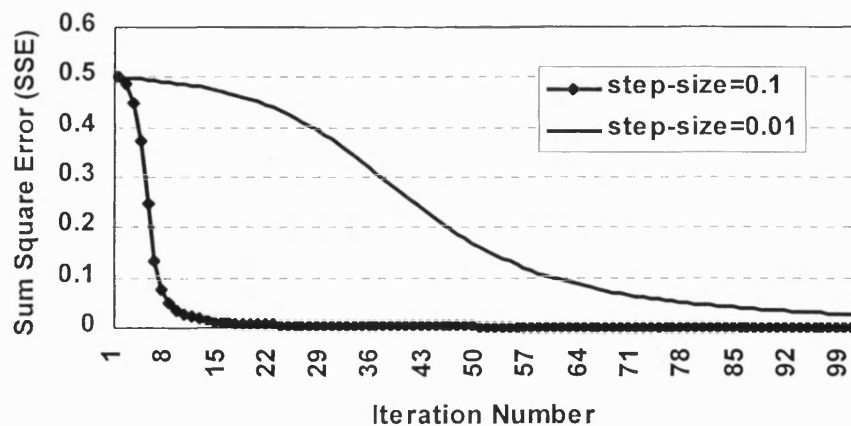
Figure 4. 10: The Sum-Square Error (SSE) of a typical multi-layer perceptron neural network.

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A simple method of increasing the rate of learning and avoiding the danger of instability is to modify the equation **(4-24)** by including a momentum term as below:

$$w_{ji}^{(l)}(n+1) = w_{ji}^{(l)}(n) + \alpha\delta_j^{(l)}(n)y_i^{(l-1)}(n) + \lambda\left[w_{ji}^{(l)}(n) - w_{ji}^{(l)}(n-1)\right] \qquad (4\text{-}25)$$

In equation **(4-25)**, λ is a positive number, which is called the momentum constant. It controls the effect of updating interconnection weights rate in last iteration on the current iteration.

♦ *Iteration*: Iterate the computation by showing new patterns of training examples to the network until the free parameters of the network stabilise their values. In this case, the average sum square error is at a minimum or accepted small value.

4.6 Dynamical Considerations of the Recurrent Neural Network

As has been noted in section 4.4.3, the recurrent neural network includes at least a feedback loop in its structure and this enables it to store information about time in a dynamically stable configuration.

The dynamical behaviour of a recurrent neural network that includes N neurons, is uniquely described by a parameter set $\{W, I\}$. $W = \{w_{ij}\}$ is an $N \times N$ matrix whose element w_{ij} is the connection weight between the jth and the ith neurons. $I = \{I_i\}$ is a vector whose element I_i is the external input to the ith neuron. Let $u_j(t)$ denote the input and $x_j(t)$ denote the output of activation function in neuron j. These two variables are related by:

$$x_j = \varphi(u_j) \qquad (4\text{-}26)$$

In equation **(4-26)**, $\varphi(\cdot)$ is the sigmoid non-linearity of neuron j. By making the assumption of symmetrical connection weight described by $w_{ji} = w_{ij}$, the state of neuron j can be described in terms of the output signal $x_j(t)$ and in this situation, the dynamics of the recurrent neural network is described by a set of non-linear differential equations as follow [4-17]:

$$C_j\frac{du_j}{dt} = \sum_{\substack{i=1 \\ i \neq j}}^{N} w_{ji}\varphi_i(u_i) - \frac{u_j}{R_j} + I_j \qquad j=1,2,\ldots\ldots,N \qquad (4\text{-}27)$$

In equation (4-27), C_j shows the capacitive effect[2] associated with neuron j, R_j is the leakage due to the finite input resistance of the non-linear element of neuron j, and I_j is an external input to the neuron j. For simplicity, the amounts of capacitance, resistance and activation function for all neurons are assumed the same and by these assumptions, the equations of motion become:

$$\frac{du_j}{dt} = \sum_{\substack{i=1 \\ i \neq j}}^{N} w_{ji} \varphi\left(u_i\right) - \frac{u_j}{\tau} + I_j \qquad j=1,2,\ldots\ldots,N \qquad (4\text{-}28)$$

It is shown that the equations of motion for a network with symmetrical connection weight, $w_{ji}=w_{ij}$, always lead to a convergence to stable state. In this situation, the outputs of all neurons remain constant. The stable states are the minimum of the quantity, which is called energy function. An energy function, which is bounded from below and is non-increasing when the state of network changes [4- 18], is defined as below:

$$E(t) = -\frac{1}{2} X^T(t)\, W X(t) - I^T X(t) \qquad (4\text{-}29)$$

Hopfield [4- 17] showed that when the non-linear functions in the neurons are bounded, monotonically increasing, and continuous, and the connection weights are symmetric, the dynamics of the recurrent neural network always lead to a stable state such that the energy function, E, is minimum. Consequently, if the network is started in any initial state, it will move in a downhill direction of the energy function until it reaches a minimum.

Making the assumption of symmetrical connection weights and using the ability of the recurrent neural network to solve the optimisation problem in the multi-user detection, the energy function described by equation (4-29) can be written as [4- 17]:

$$E = -\frac{1}{2} \sum_{i} \sum_{\substack{j \\ i \neq j}} w_{ji} x_j x_i - \sum_{j=1}^{N} x_j I_j \qquad (4\text{-}30)$$

---

[2] This effect is an intrinsic property of biological neurons or the physical implementation of artificial neurons.

In equation **(4-30)**, also it is assumed that the self-connection weight w_{ii} is set to zero and under this assumption the state of network always converges to a corner of a hyper cube in the signal space where x_i has the values ± 1 [4-11]. The importance of the energy function, E, is that it provides the basis for understanding of how specific problems can be solved by recurrent neural network. It is shown that the energy function is a monotonically decreasing function of the network states $\{x_j|\, j=1,2...N\}$ [4- 17]. When the network is started in any initial state, it will move toward a state that the energy function, E, reaches to a minimum point and at this point, it stop changing with time. In fact, the recurrent neural network may be viewed as a non-linear associated memory, which can remember the main stored pattern in response to the presentation of a noisy version of that pattern.

Network of neurons with this basic organisation can be employed to compute solution to specific optimisation problems. In each situation, by choosing the suitable connection weights and the input signals, the desired function could be minimised. In considering the recurrent neural network as a multi-user detector in the DS-CDMA communication system, the equations related to states of network can be changed as below:

$$\frac{du_j}{dt} = \sum_{\substack{i=1 \\ i \neq j}}^{N} w_{ji}\varphi\left(u_i\right) + I_j \qquad j=1,2...N \qquad (4\text{-}31)$$

In this equation, I_j is an external input to the jth neuron in the network, $\tau = RC$, the time constant is assumed to be infinity. The energy function term of the recurrent neural network is the same as equation **(4-30)**. The time derivative of the energy function is always negative and the state of network always converges to a corner in signal space that the energy function has a minimum value.

As an example, a recurrent neural network with $N=3$ neurons is considered. The weight matrix of the network is chosen as:

$$W = \frac{1}{3}\begin{bmatrix} 0 & -2 & 2 \\ -2 & 0 & -2 \\ 2 & -2 & 0 \end{bmatrix} \qquad (4\text{-}32)$$

The threshold level applied to each neuron is assumed to be zero and the activation of each neuron is sign function. For this network there are $2^3=8$ states and only two states are stable among them. These stable states are (1, -1, 1) and (-1,1, -1) and it can be verified as below:

$$\text{sgn}[WX] = \text{sgn}\left[\frac{1}{3}\begin{bmatrix} 0 & -2 & 2 \\ -2 & 0 & -2 \\ 2 & -2 & 0 \end{bmatrix}\begin{bmatrix} 1 \\ -1 \\ 1 \end{bmatrix}\right] = \begin{bmatrix} 1 \\ -1 \\ 1 \end{bmatrix} \qquad (4\text{-}33a)$$

$$\text{sgn}[WX] = \text{sgn}\left[\frac{1}{3}\begin{bmatrix} 0 & -2 & 2 \\ -2 & 0 & -2 \\ 2 & -2 & 0 \end{bmatrix}\begin{bmatrix} -1 \\ 1 \\ -1 \end{bmatrix}\right] = \begin{bmatrix} -1 \\ 1 \\ -1 \end{bmatrix} \qquad (4\text{-}33b)$$

As can be seen in equations **(4-33a)** and **(4-33b)**, both of these states are stable. By calculating the energy function according to the equation **(4-30)**, it can be shown that the minimum level of the energy function is belongs to these stable states with $E = -2$. For other states, the level of energy function is 2/3.

4.7 Multi-Layer Perceptron Neural Networks as DS-CDMA Receivers

An interesting and important way in designing the multi-user receivers in the direct-sequence CDMA communication is the design of adaptive systems, that self-tune the detector parameters from the observation of the received signal. The multi-layer structures of neural networks potentially have this ability to work as the adaptive receivers in this environment. They have the capability to perform subtle decision boundaries via training to separate the wanted and unwanted signals. For this purpose, a multi-layer perceptron has been trained to demodulate DS-CDMA waveforms. The training is an iterative process of modifying the interconnection weights and thresholds of neurons to minimise an error function.

In this section, the feedforward multi-layer adaptive neural network receivers for direct-sequence CDMA system are considered. It is observed that the proposed receivers are able to despread the desired signal, suppress the effect of multipath, reject the MAI, and combat the effect of the 'Near-Far' problem. It can be seen that the proposed receivers have acceptable performance in different channel model scenarios.

4.7.1   The Adaptive MLP Neural Network Single-User Receiver

Figure 4. 11 shows the structure of a feedforward multi-layer neural network for implementing the DS-CDMA receiver. After converting the received signal to the baseband, it passes through a chip-matched filter and is sampled at the end of every chip interval. These samples are fed into the taped-delay line that converts the serial received signal to a parallel form. The number of taps in the delay line is equal to the period of signature waveform, in the usual way. The output signals of taped-delay line are fed into the input layer. Let w_{li} be the connection weight from the ith node in the input layer to the lth node in the hidden layer and θ_l is a threshold associated with the lth node in the hidden layer. The output signal of lth node in the hidden layer is [4-13]:

$$O_l = \varphi\left(\sum_{i=1}^{N} w_{li} x_i + \theta_l\right) \tag{4-38}$$

In equation (4-38), x_i is the input signal from i^{th} input node and N is the number of input nodes. $\varphi(.)$ is the activation function, which has the form:

$$\varphi(x) = \tanh(x) \tag{4-39}$$
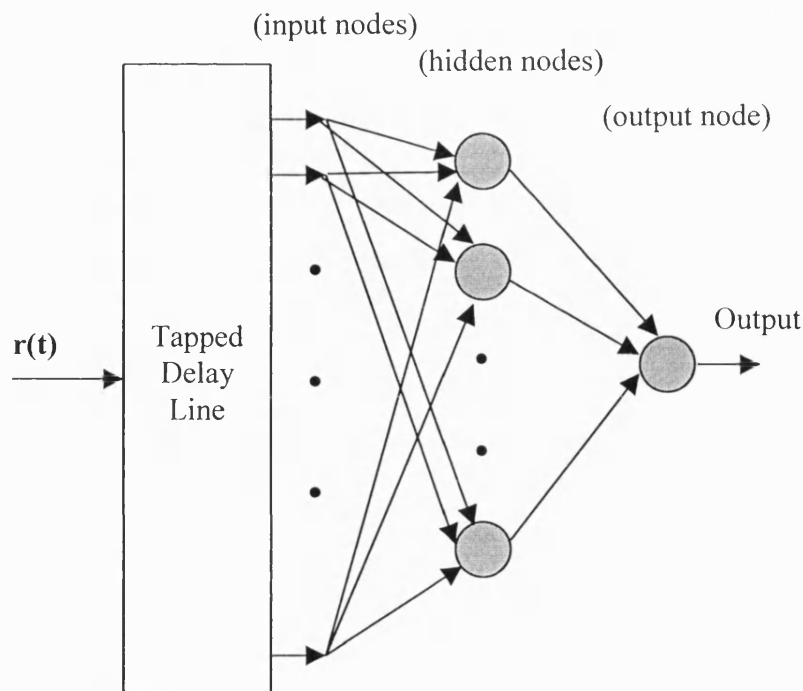
Figure 4. 11: The structure of a feedforward multi-layer perceptron neural network for implementing the DS-CDMA receiver.

Let w_{jl} be the connection weight from the lth node in the hidden layer to the jth node in the output layer, O_l is the output of the lth hidden layer and Φ_j is a threshold associated with the jth node in the output layer. The output from the jth output layer is:

$$O_j = \varphi\left(\sum_l w_{jl}O_l + \phi_j\right)$$ (4-40)

The interconnection weight values are updated during training mode via the 'back-propagation' training algorithm, which performs the steepest descent on a surface in weight space. For example, the weight value from the lth node in the hidden layer to the jth node in the output layer, w_{jl}, is updated as follows:

$$w_{jl}(k+1) = w_{jl}(k) - \alpha \cdot \delta_{jl} \cdot O_l$$
$$\delta_{jl} = (1 - O_l^2) \cdot (T_l - O_l)$$ (4-41)

Here, T_l is the desired output and α is the step-size. On the other hand, the weight value from the ith node in the input layer to the lth node in the hidden layer, w_{li}, is updated as the pervious way with δ_{li} as follows:

$$\delta_{li} = (1 - O_l^2) \cdot \sum_j \delta_{jl}w_{jl}$$ (4-42)

The performance of the adaptive MLP neural network receiver in the different channel model scenarios in the DS-CDAM environment will be investigated in chapter six.

4.7.2 The Adaptive MLP Neural Network Multi-User Receiver

By using a bank of matched filter in front of the adaptive neural network receiver and increasing the number of neurons in the output layer, an adaptive multi-user neural network receiver is realised. Figure 4. 12 shows the structure of this receiver.
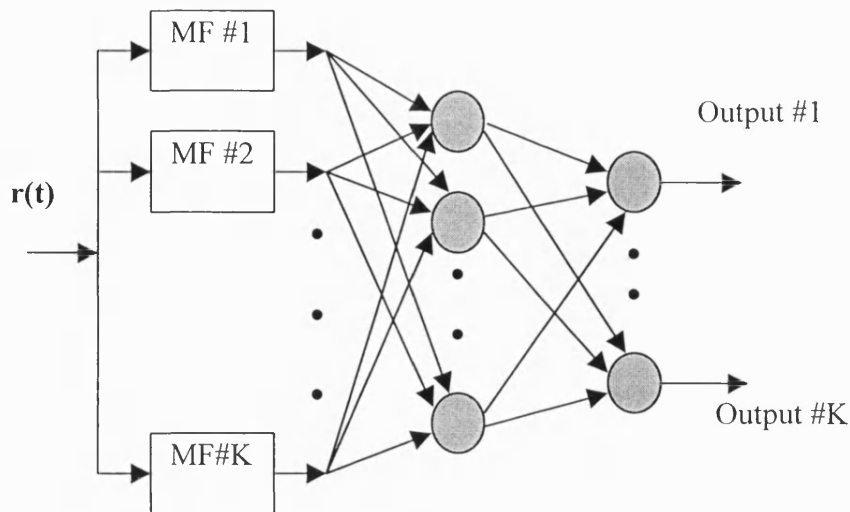
Figure 4. 12: The structure of the adaptive multi-user MLP neural network receiver.

The number of matched filters and neurons in the output layer are equal to the number of co-channel users. The output of matched filters are fed into the input layer and the value of weights are updated during training mode via the 'back-propagation' algorithm, corresponding to the equations **(4-38)**, **(4-34)**, **(4-41)** and **(4-42)**.

In chapter six, the BER performance of the adaptive multi-user MLP neural network will be evaluated and compared with other types of multi-user DS-CDMA receiver.

4.8 The Recurrent Neural Network as DS-CDMA Receiver

Multiple access interference (MAI) produced by the other co-channel users is a major limitation to the capacity of a DS-CDMA system. A potential solution to this problem, particularly when used in the base-station in the uplink channel, is the optimum maximum-likelihood multi-user detector. The computational complexity of this detector increases exponentially with the number of co-channel users and however it is currently too complex to be implemented in commercial systems.

Sub-optimal detectors such as the decorrelating receiver are proposed to reduce the effect of MAI. These types of receivers have a computational complexity, which only grow linearly with the number of co-channel users. The major disadvantages of these receivers, however, are the high computational complexity resulting from having to invert the correlation matrix of users'

signature waveforms in the real time. A particularly interesting method of multi-user detection, which has the potential for low computational complexity, is the application of neural network concepts. Miyajima [4-11] proposed a recurrent neural network for multi-user detection that uses the likelihood function as the energy function to be minimised.

In this section, a recurrent neural network receiver with low implementation complexity for DS-CDMA systems is investigated and a comparative performance analysis with the conventional matched filter receiver, the optimum multi-user receiver and the decorrelating detector are carried out via a Monte Carlo simulation in chapter six. It will be observed that the proposed receiver is able to combat the effect of MAI and has acceptable performance in different channel models scenarios.

4.8.1 The Structure of Recurrent Neural Network as a Multi-User Detector

After converting the received signal to the base-band, it passes through a chip-matched filter and is sampled at the end of every chip interval. These samples are fed into a bank of matched filters. The number of matched filters in the filter bank is equal to the number of co-channel users, K. The outputs of the matched filters are sampled every bit interval and are fed into the input section of the recurrent neural network.

The recurrent neural network has a structure that consists of a number of small non-linear processing units. Each unit contains a summer and a non-linear function. The output of each unit is fed to all other units via connection weights and each unit has an external input. The structure of the recurrent neural network multi-user receiver is shown in Figure 4. 13.

Hopfield [4- 17] showed that, when the connection weights are symmetric, the dynamics of the recurrent neural network always lead to a stable state where the energy function, E, is minimum.

$$E = -\frac{1}{2}\sum_{i}\sum_{\substack{j \\ i \neq j}} w_{ji}x_j x_i - \sum_{j=1}^{N} x_j I_j \qquad (4\text{-}54)$$

In equation **(4-54)**, E is the energy function, x_j is the output signal of the jth unit, I_j is the external input signal to the jth unit, w_{ji} is the value of connection weight from the jth to the ith unit and N is the number of units.
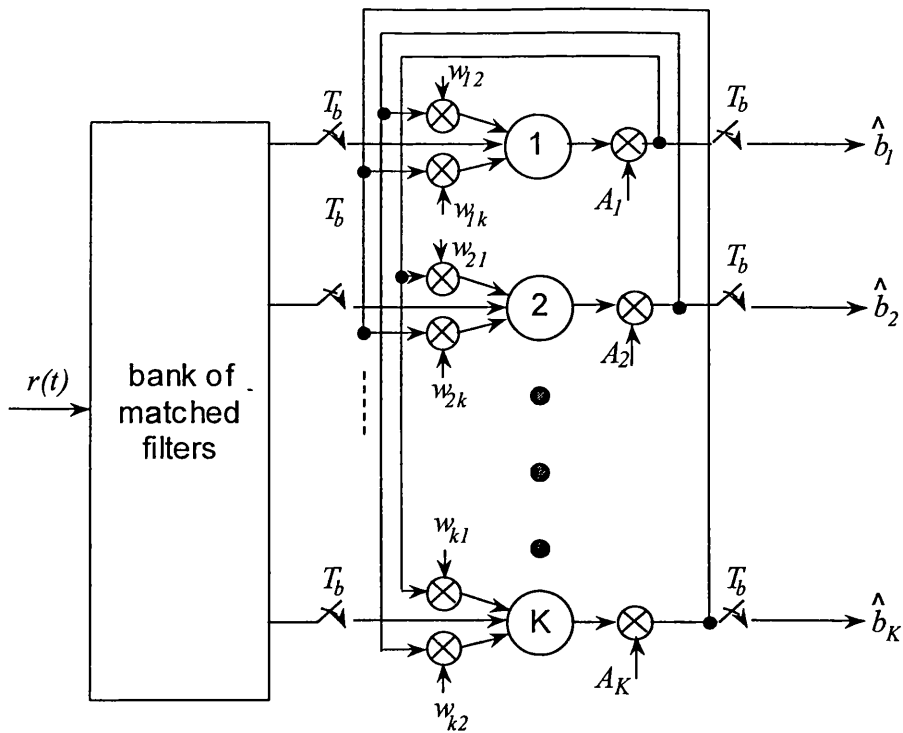
Figure 4. 13: The structure of the recurrent neural network receiver.

By comparing the equation (2-23) in chapter two, which interprets the maximum-likelihood criterion, with equation (4-54), it can be seen that the optimum multi-user detector can be implemented by the recurrent neural network structure if $I_j=2Y_j$, $x_j=A_jb_j$, $N=K$, and $w_{ji} = -2h_{ji}$. In this situation, the recurrent neural network structure can be employed as a multi-user detector in the multiple-access environment. The recurrent neural network receiver uses the outputs of the bank of matched filters as external inputs to the neural network. It also employs the cross-correlation of different users' signature waveforms and the amplitude of the received signals as parameters in its structure. The self-connection factor w_{kk} was selected to be zero. Under this assumption, the system will always converge to a corner in the signal space with minimum energy level and has a global minimum [4- 17].

The ability of the recurrent neural network receiver to detect the DS-CDMA signals in the multi-user environment and to combat the effect of co-channel other user interference will be verified in chapter 6. In this way, the BER performance of the optimum maximum-likelihood receiver, the recurrent neural network receiver, the conventional matched filter receiver and the decorrelating receiver will be compared. It will be shown that the recurrent neural network receiver has remarkable performance in the different channel model scenarios and is a good

candidate to be implemented as a multi-user receiver in the DS-CDMA multiple-access environment.

4.9 Summary

In this chapter the application of the neural network structures for implementing the DS-CDMA receivers in a spread spectrum communication system have been considered. It has been shown that artificial neural networks are suitable candidates for use as detecting the transmitted data in the multiple-access DS-CDMA environment. In this case, two popular structures of the neural network, which are called the multi-layer perceptron and the recurrent neural network, have been shown to have good characteristic for use as receivers in these systems. The MLP neural network is an adaptive system, which learns via training to detect the wanted pattern (desired user's signature waveform) and reject the unwanted patterns (co-channel other user's signature waveforms). The recurrent neural network receiver has a dynamical behaviour, which is uniquely described by a parameter set $\{W, I\}$. $W=\{w_{ij}\}$ is a matrix whose elements w_{ij} are the connection weights between the jth and the ith neurons. $I=\{I_i\}$ is a vector whose elements I_i are the external inputs to the ith neurons. In this case, by choosing suitable values for W and I, the recurrent neural network receiver is changed into a multi-user receiver in the DS-CDMA environment.

The performance of these receivers in the DS-CDMA multiple-access environment will be considered in chapter six. It will be shown that the adaptive multi-layer perceptron neural network receiver provides signal despreading, combats multipath-fading and MAI as well as the effect of unequal power control resulting from the 'Near-Far' effect. Also, it will be shown that this receiver through training process, learns to collect different rays of signal propagation in the multipath channel and maximise the energy of the desired user's signal and minimise the cross-correlation of other users' signals in the multiple-access DS-CDMA channel. The learning speed of the adaptive neural network receiver is high and it has extremely good stability during fast training mode. Also, it will be shown that the recurrent neural network receiver is extremely suitable for combating the effect of co-channel interference in a multiple-access environment. In addition the implementation complexity of the recurrent neural network is very low. The good performance and low implementation complexity of the recurrent neural network receiver makes this receiver attractive for the next generation of wireless multimedia systems.

4.10 References

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Chapter Five

DS-CDMA System Simulation

5.1 Introduction

In this chapter, the DS-CDMA system is described that has been simulated via a Monte-Carlo simulation technique by using Visual C^{++} software on computer. In order to receive the desired user's signal, two different situations for the receiver are assumed. In the first case, it is assumed that the desired user's receiver is a mobile handset and receives the signal through a downlink 'base-to-mobile' channel which includes co-channel other users' signals. It is clear that in this situation, a single-user strategy should be employed for implementing the receiver. Figure 5. 1 shows the block diagram of the transmitter, channel and receivers of this system in the DS-CDMA communication environment. As is shown, in order to evaluate the performance of the single-user receivers in this environment, several types of receiver including the conventional matched filter receiver, the RAKE receiver, the adaptive MMSE receiver and the adaptive multi-layer perceptron neural network receiver have been implemented in the destination unit.

In the second case, it is assumed that the desired user's receiver is located in a stationary base-station and receives its signal through an uplink 'mobile-to-base' channel which includes the co-channel other users' signals. In this situation, the strategy is to employ the multi-user receiver, where it has all additional information about the signature waveform, the received signals' amplitudes and timing of all co-channel users. Figure 5. 2 shows the block diagram of the transmitter, channel and receivers of this system in the DS-CDMA communication environment. It is shown that for evaluating the performance of the multi-user receivers in this environment, several types of receiver, including the maximum-likelihood receiver, the decorrelating receiver, the MLP neural network receiver and the recurrent neural network receiver have been implemented in the destination unit.

This chapter contains a description of the DS-CDMA system, which has been implemented to evaluate the performance of different receivers. In this way, different parts of this system, which are shown in Figure 5. 1 and Figure 5. 2, will be explained in the next sections. In the following sections, the data generation, modulation, signature waveform generation and the simulation of transmission channel in the DS-CDMA system are described. Data reception in the DS-CDMA environment is the subject of the sixth section, in which the implementation of different types of receiver is considered. The summary of the chapter comes in the final section.
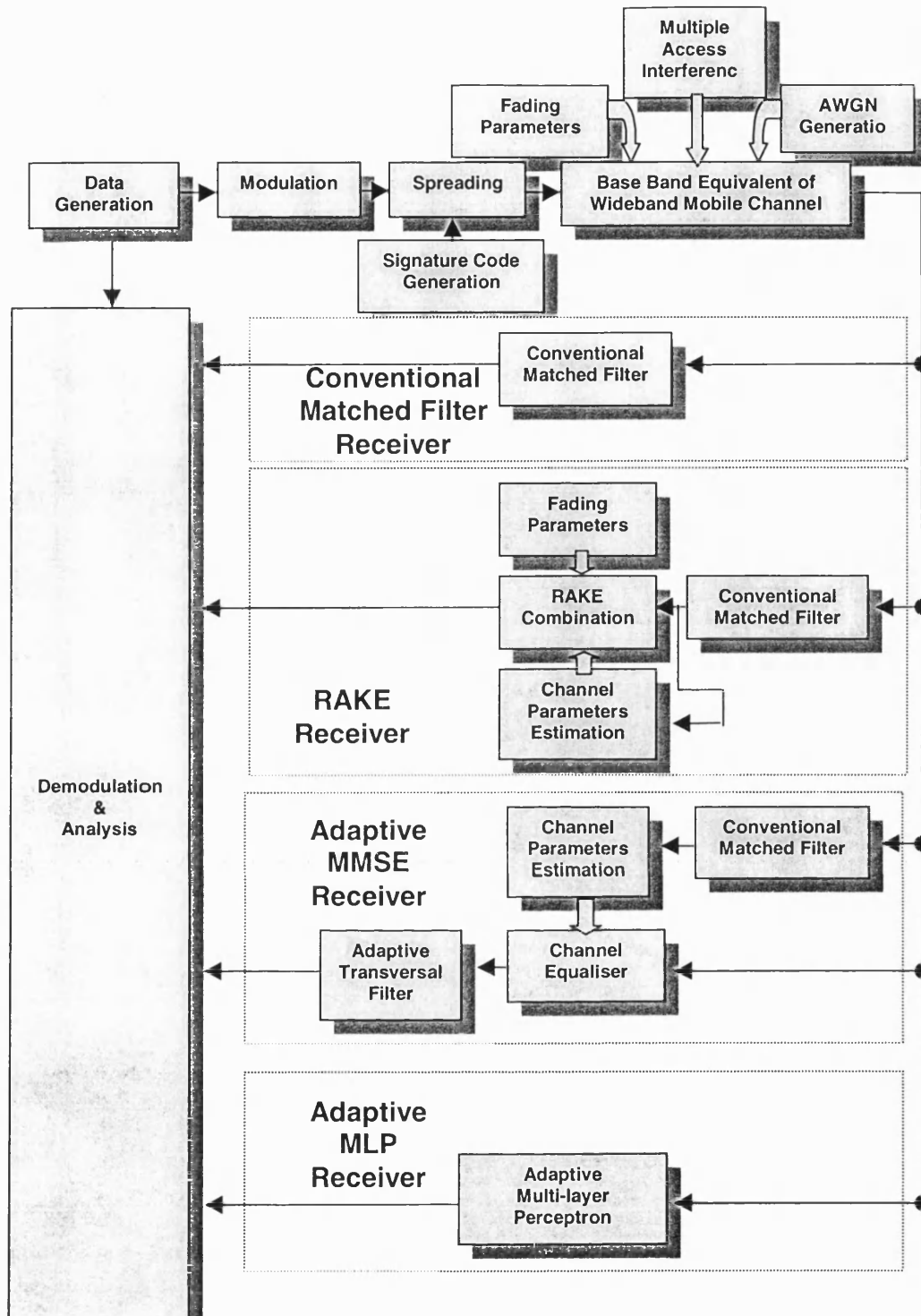
Figure 5. 1: The block diagram of the simulated system for the downlink channel.
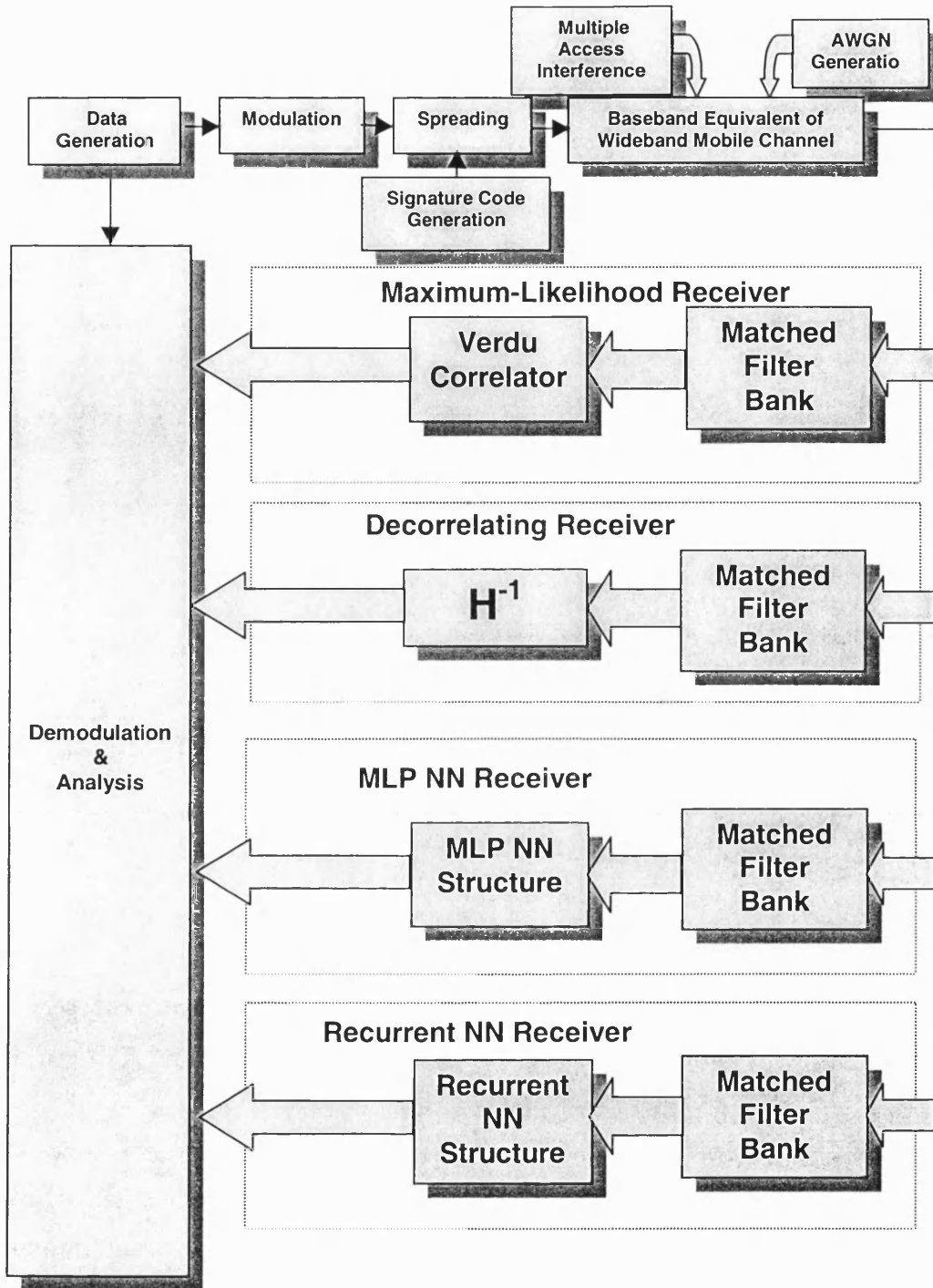
Figure 5. 2: The block diagram of the simulated system for the uplink channel.

5.2 Data Generation

In order to transmit the random data for a DS-CDMA system, random binary sequence which has been obtained from an independent source, is used. A random binary sequence consists of a statistically independent sequence of 0's and 1's each occurring with the probability of ½. As it is considered in the Appendix A, a pseudorandom sequence (PN) is a periodic sequence with period 2^n-1 where n is the number of stage in the feedback shift register. The auto-correlation function of a PN sequence is very similar to the auto-correlation function of a random binary sequence [5-1].

Due to the good performance of the PN sequences for use as the random binary data, a feedback shift register with n=18 stages (period=262143) is implemented to generate the random data bits. The structure of this random data bit generator is shown in Figure 5. 3.
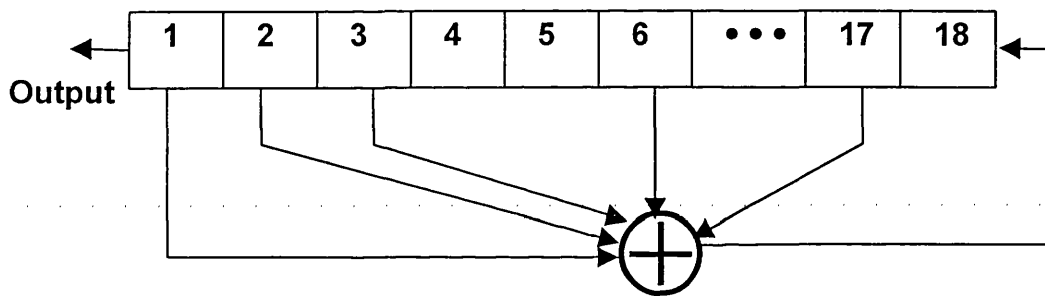
Figure 5. 3: The structure of a feedback shift register for generating the ML code sequence.

As can be seen, it includes a taped-delay-line shift register with 18 serial cells and a summer[1]. The summer adds the output bits of several selected cells and a feedback line returns the result to the final cell. The selected taps, which are determined in the structure of the feedback shift register to generate a special ML sequence, can be interpreted with a polynomial as below[2]:

$$m^{18} \oplus m^5 \oplus m^2 \oplus m \oplus 1 \qquad\qquad\qquad (5\text{-}1)$$

---

[1] It is a digital summer.

[2] In equation (5-1), $\oplus$ means modulo two addition.

This feedback shift register with different initial values, which are called seeds, is employed for generating the random data bits for all co-channel users in the DS-CDMA channel. In is noted, with this assumption, the binary random sequences of all co-channel users will be statistically independent.

5.3 Modulation

In order to modulate the random data bits, two types of the PSK modulation schemes have been employed in the simulation. In the binary phase shift keying (BPSK) modulation, the carrier is modulated according to:

$$r(t) = b(t) \, cos(\omega_0 t) = \pm cos(\omega_0 t) \tag{5-2}$$

In equation **(5-2)**, $b(t)$ is the bipolar data to be transmitted at time t and ω_0 shows the carrier frequency. In this case, the polarity of the amplitude of sinusoidal carrier signal is changed according to the value of random data bit.

The differential BPSK (DBPSK) is another technique for data modulation, where the random data stream is differentially encoded. This scheme of modulation combats the phase ambiguity problem and it has been employed when the RAKE receiver was implemented in the multipath channel. The encoding process in the DPSK modulation scheme is as below:

$$b'(i) = b'(i-1) \oplus b(i)$$
$$r(t) = b'(t) cos(\omega_0 t) = \pm cos(\omega_0 t) \tag{5-3}$$

In equation **(5-3)**, $b(i)$ is the ith binary data bit and $b'(i)$ is the ith coded data bit. The decoding process in the receiver is very similar to the encoding process in the transmitter. It can be done as below:

$$\hat{b}(i) = \hat{b}'(i) \oplus \hat{b}'(i-1) \tag{5-4}$$

In equation **(5-4)**, $\hat{b}'(i)$ is the ith received data and $\hat{b}(i)$ is the ith decoded data.

5.4 Generation of Signature Waveform Sequences

In a DS-CDMA communication system, each user in the channel is associated with a signature waveform which is used for spreading the modulated signal. In this way, two popular sets of the PN sequences, the ML and the Gold codes, are employed. The main factor for selecting a set of signature waveform is the value of the cross-correlation between different pairs of the set. The set with lower cross-correlation is better than the set with higher cross-correlation because it generates lower co-channel interfere in the communication channel. As is shown in Appendix A, using Gold codes [5- 2], [5- 3] as the signature waveforms is quite common because they can have good cross-correlation properties and are suitable for use in the DS-CDMA communication systems. Hence a set of Gold codes has been employed as the signature waveform of the desired and co-channel users in the channel.

In the simulation, the Gold codes are generated by modulo two addition of a preferred pair of the ML codes. Two feedback shift registers generate a preferred pair of the ML codes and this preferred pair has been chosen from the table, which is produced by Peterson and Weldon [5-4]. Two polynomials that show the location of the determined taps in the feedback shift registers are as below:

$$m^5 \oplus m^2 \oplus 1 \qquad \text{and} \qquad m^5 \oplus m^4 \oplus m^2 \oplus m \oplus 1 \tag{5-5}$$

In this situation, the length of each shift register is $n = 5$, and the number of chips per bit in the sequences equals to $2^n\text{-}1 = 31$ and hence the processing gain (PG) of the direct-sequence spread spectrum system is 31. The number of the Gold codes in the code set is $2^n + 1 = 33$ and this is the upper limit on the number of co-channel users in this DS-CDMA communication system.

For normalising the energy of each bit in the sequence, the amplitude of each chip in the signature waveform is determined as $\pm \dfrac{1}{\sqrt{PG}}$ and hence the energy of each bit is normalised to:

$$PG \times \left(\pm \frac{1}{\sqrt{PG}} \right)^2 = 1 \tag{5-6}$$

5.5 Simulation of the Transmission Channel

After spreading the information data of each user with a signature waveform from the Gold code set, these signals are applied to the base-band equivalent model of a wide-band mobile channel model, which is introduced in Appendix B. The COST207 model of the channel describes the channel impulse response in terms of a set of Doppler characteristics (fading weights) at various specified time delays. The channel model, which has been developed to simulate the COST207, simply consists of a tapped-delay-line of variable length. This model uses six taps, which can be irregularly spaced according to the GSM model of the channel impulse response. In the simulation, it is assumed that the frequency of the carrier is 900 MHz and the chip rate of signal equals to 3.1×10^6 chips/sec. According to these assumptions, the minimum delay space in the channel is approximately 0.2 μsec. The output signal of each tap is multiplied by a time varying coefficient that characterises the fast fading. It is then multiplied by a further gain, which represents the average multipath signal strength expected at that delay. The weighting factors are chosen from the urban impulse response model in Fig. B. 4, which is known as the COST207 model. Then the output signals of all taps are added together using a complex summer. The fast fading coefficients are produced using six independent complex additive white Gaussian noise generators. The mobility of the user is incorporated into the channel through the Doppler frequency of the Rayleigh fading statistics. For example, a 100 Hz Doppler frequency at a 900 MHz carrier frequency interprets as a vehicle speed of 120 km/h. The Doppler effect is generated by shaping the AWGN using a classical Doppler filter. A cascade structure of two-second order filters is employed to approximate the frequency domain transfer function of the Doppler filter, which is explained in Appendix B.

The shaped noise is obtained by passing the AWGN via the Doppler filter and the Rayleigh fading is produced by the fact that the independent Gaussian fading on both the real and the imaginary weighting components are used. To implement the static multipath channel, fixed weighting factors are employed for each of 6 taps in the channel model.

Adding all users' signals synchronously or asynchronously performs MAI, which shows the effect of other co-channel interference users. In asynchronous mode, the phase shifts of all users have a uniform distribution between zero and 31 chips. The power of the interfering signals can be made different by changing the amplitude of the received signals in the simulating program.

Finally, the thermal noise as AWGN is added to the multi-user channel. The noise samples have a normal distribution and are derived from a uniform random sequence by the Box-Muller

transformation [5- 5]. According to equation **(5-6)**, it is assumed that the energy of each random data bit is normalised to one and by changing the variance of the noise samples, the E_b/N_0 can be set to the required value in the simulation programs.

5.6 Reception of DS-CDMA Signals in a Cellular Environment

In this section, different types of receiver for detecting the transmitted data bits in a DS-CDMA environment, are described. As has been noted in section **5.1**, in order to receive the desired user's signal, two different situations are assumed. In the first case, the downlink channel is a physical environment that transfers the information signals from a base-station to the mobile handset. In this situation, the receiver is a single-user detector, which tries to determine the data bit of the desired user in a multiple access DS-CDMA channel. The receiver should be able to resist against the MAI with 'Near-Far' effect in a multipath-fading environment.

In the second case, the uplink channel is a physical environment that transfers the information signals from mobile handsets to the base-station. In this situation, the receiver is a multi-user detector, which tries to determine the data bit of all co-channel users in the multiple-access channel.

The first group of receivers, which has been implemented in this simulation for the downlink channel, includes the conventional matched filter receiver, the RAKE receiver, the adaptive MMSE receiver and the adaptive MLP neural network receiver. The second group contains receivers including the maximum-likelihood receiver, the decorrelating receiver, the adaptive MLP neural network receiver and the recurrent neural network receiver.

5.6.1 The Conventional Matched Filter Receiver

The first receiver for the downlink channel, which has the simplest structure, is the conventional matched filter or digital matched filter receiver. In this receiver, the received signal is multiplied by the local PN signature waveform sequence, where the perfect synchronisation is assumed. This PN signature waveform sequence is a replica of the signature waveform, which has been employed at the transmitter to spread the desired user's signal. After it, the post-correlation signal goes to the BPSK base-band demodulator. This block performs the operations of integration over a bit periods, T_b, sampling the output of the integrator at the bit rate, and finally contains the decision circuit. The conventional matched filter receiver is the

solution of the maximum-likelihood criteria in a single-user AWGN DS-CDMA channel and it has the best performance in this case. The BER performance of this receiver in this situation is a good reference for evaluating the performance of other single-user interfere rejecting receivers in the multiple-access environment.

This receiver has a simple structure and it is very useful to understand the despreading process in the spread spectrum communication. All parts of this receiver are used in the structure of the RAKE receiver. It is noted that the conventional matched filter receiver is equivalent to one branch of the RAKE receiver.

5.6.2 The RAKE Receiver

In the multipath channel, the conventional matched filter receiver is unable to collect the distributed energy from the different delayed echoes in the channel. In this case, the RAKE receiver is a suitable receiver that can be employed. The RAKE receiver has been implemented in this work to combat the effect of the multipath channel in the DS-CDMA environment. The structure of this receiver has been designed to achieve the multipath combining of the received signal. The general structure of the RAKE receiver is shown in Figure 5. 4. As it is shown, it has been implemented by using a digital delay line, which is located at the output of the local signature waveform generator to provide delayed samples of the despreading signature waveform. It is supposed that the relative delays between the multipath components are a factor of chip period, T_c.

At the output of the matched filter, there are several lines corresponding to the number of taps in the multipath channel, with complex values. At this point, the delay profile and attenuation coefficients of the multipath channel should be known or estimated. In the case of static multipath, the characteristics of the channel can be estimated via a channel sounding preamble or real using data transmission via a decision directed channel estimation. In this case, the impulse response of the multipath channel can be determined and the RAKE receiver can be implemented perfectly. In the case of dynamic multipath, the impulse response of the channel is varying and the estimation of the channel's parameters must be done during the real data transmission.
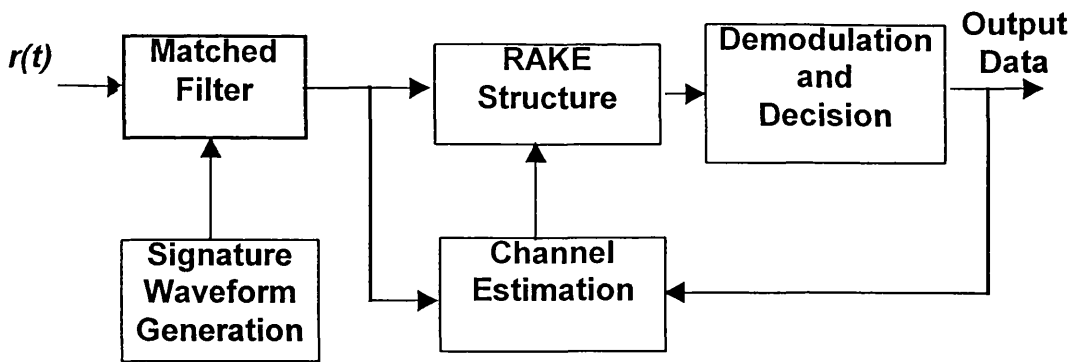
Figure 5. 4: The general structure of the RAKE receiver.

It is known that the Maximal Ratio Combining (MRC) and the Equal Gain Combining (EGC) [5- 6] are two famous combination techniques, which can be employed to estimate the parameters of the multipath channel and to implement the RAKE receiver[3]. The combining process can be performed with the post-correlation signal and the known or estimated channel impulse response. The arrived signals at each of the RAKE arms have been despread by an appropriately delayed version of the desired user signature waveform. Figure 5. 5 shows the detailed structure of the RAKE receiver, which has been implemented in the simulation.
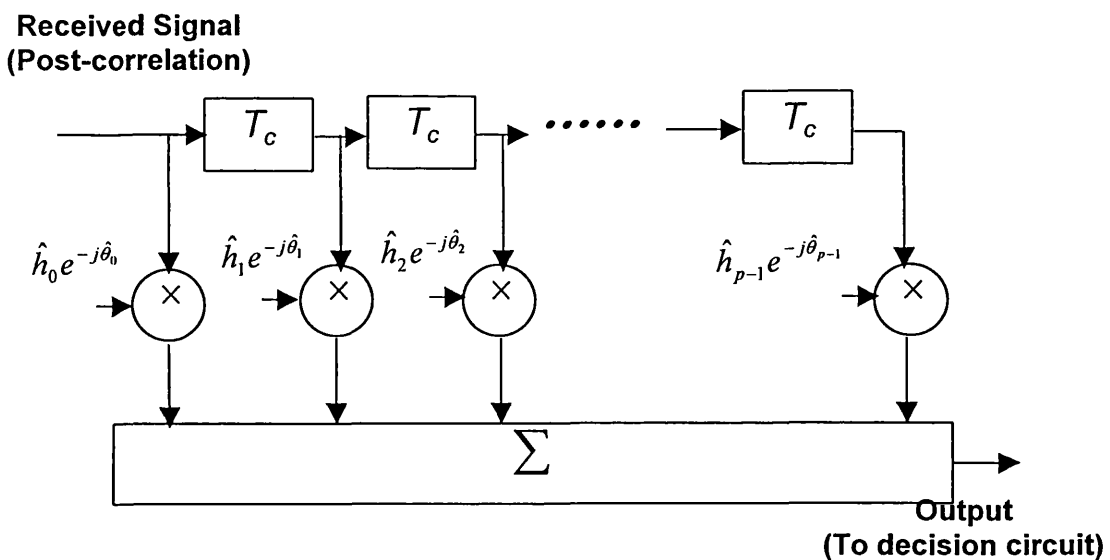
Figure 5. 5: The detailed structure of the RAKE receiver.

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[3] These techniques will be explained in Appendix B.

The detailed structure of the RAKE receiver is performed by using multipliers, which multiply each branch of the post-correlation signal with the corresponding complex conjugate estimate of the channel's impulse response, and a summer, which sums all of the signals at the output of multipliers [5- 6]. The RAKE filter coefficients are an estimate of the channel impulse response, and $\hat{h}_k(n)e^{-j\hat{\theta}_k(n)}$ is an estimate of the kth multipath branch for the nth transmitted bit. The signal at the output of the RAKE filter is applied to the decision circuit, where the signal is demodulated, is integrated over a bit period and subsequently sampled, and is decided as a bit. This bit is feed back to the channel estimator for use in the next estimation.

5.6.3 The Adaptive MMSE Receiver

The MMSE receiver is the third receiver for the downlink channel, which has been implemented in the simulation to receive the desired user's signal in the multipath channel in a DS-CDMA environment. After converting the received signal to the base-band, and passing through a chip-matched filter, it is sampled at the end of every chip interval. These samples are fed into the adaptive filter, which has been implemented as a tapped-delay-line structure. The output of the adaptive filter is sampled once every bit interval and passed through a hard limiter to estimate the data bit. Tap weights in the adaptive filter are updated once every bit interval and an error signal that is the difference between the desired signal and the output signal of the transversal filter, in an adaptive algorithm, controls the weight updating process.

To simulate the structure of the adaptive MMSE receiver in a DS-CDMA environment, a delay line with 31 cells has been implemented. The 31 complex weights of the adaptive receiver have been set to zero in the beginning of the training process and have been updated once every bit interval by an adaptive algorithm during training and data bit transmission.

To train the adaptive MMSE receiver, known data sequences are inserted into the transmitted data stream for the desired user at the start and at regular interval[4]. As the chosen sequence must be known at both the transmitter and the receiver, a suitable candidate is the pseudorandom signature waveform of the desired user. It can be transmitted at the symbol rate for training purpose.

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[4] In the case of static channels, the training sequences are used only in the beginning of real data transmission.

Increasing the mobility of the mobile receiver reduces the performance of the adaptive MMSE receiver in a multipath-fading channel. In this case, it is needed to compensate the effect of fading on the received signal. A channel equaliser is located in front of the adaptive MMSE receiver to remove the effect of time varying channel on the desired user's signal by estimating the delay profile and the attenuation coefficients of the multipath-fading channel. It is shown that this equaliser is able to help the adaptive part of the receiver to combat the effect of multipath-fading channel and remove the effect of co-channel interference simultaneously. In this case, it is needed to send regular training sequences related to the desired user during the real data transmission to decrease the error of the estimation process. These training sequences are helpful for adaptive part of receiver to be locked to the phase variation of the desired user's signal.

5.6.4 The Adaptive MLP Neural Network Receiver

The adaptive multi-layer perceptron neural network receiver is the fourth receiver for the downlink channel, which has been implemented by simulation to receive the desired user's signal in the DS-CDMA environment. It is known that the decision boundaries in a multi-user DS-CDMA communication environment are nonlinear and in this case, the neural network structures that include non-linear units, are able to generate decision areas with non-linear boundaries to separate the wanted and the unwanted signals.

For the downlink channel, where the receiver needs to detect the desired user's transmitted data, the adaptive MLP neural network receiver is very useful. In this case, the training sequences can be used for adjusting the receiver's parameters in a way to detect the desired user signal in a multiple-access DS-CDMA channel. The MLP neural network receiver as a single-user detector is trained on the chip basis of the desired user signature waveform as a wanted pattern and other co-channel signature waveforms as unwanted patterns. In this situation, it needs to receive the desired user and other co-channel users' signature waveforms during training process and by modifying the interconnection weights in its structure, establishes the boundaries in the decision space to separate the desired user signal from MAI.

In order to employ the adaptive MLP neural network in the multipath environment, it is necessary to introduce the delay profile of the main echoes in the multipath channel to the MLP neural network receiver during the training process. In this case, the delay profile of the main echoes should be known or determined via accurate sounding of the multipath channel.

5.6.5 The Maximum-Likelihood Receiver

The first multi-user receiver is the maximum-likelihood receiver that has been implemented by simulation of the uplink channel. The maximum-likelihood or optimum receiver is a multi-user receiver, which maximises the probability of detection of all users' data in a DS-CDMA multiple-access environment. It needs to have all information about the signature waveforms, timings, received signal amplitudes and phases of all users in the channel. When operating in synchronous mode with K co-channel users, it is implemented by using a bank of K matched filters followed by a detector that computes the 2^K correlation metrics of all possible combinations of the transmitted data and it selects the combination corresponding to the largest correlation metrics. When the system is operating in asynchronous mode, the maximum-likelihood receiver must compute 2^{KL} correlation metrics to determine the K block of sequences, each of which has a length, L. In this case, the implementation complexity of the receiver is much higher than the synchronous mode because K and L are generally large. Viterbi algorithm [5- 7] is employed to implement the maximum-likelihood criterion in this mode and it causes a significant reduction in the computational complexity but the exponential dependence on the number of users can not be reduced.

However, the high complexity of this receiver makes it impossible for use in the practical systems in a realistic commercial environment. Neverless, the performance of this receiver is a suitable reference for comparing the ability of other multi-user receivers to combat the effect of co-channel interference in the DS-CDMA environment.

5.6.6 The Decorrelating Receiver

One sub-optimum multi-user receiver that has a linear computational complexity in the number of users is the decorrelating receiver. The structure of this receiver in a DS-CDMA channel with K co-channel users, is performed by using a bank of matched filters followed with a linear mapping unit, which transfers the output of K matched filters into K data outputs. The inverse value of the correlation matrix is employed to implement the second part of the decorrelating receiver. This unit removes the effect of MAI on the received signals in the multiple-access DS-CDMA channel.

5.6.7 The Multi-User Adaptive MLP Neural Network Receiver

The adaptive multi-layer perception neural network receiver is the third receiver for the uplink channel which has been implemented by computer simulation to receive all users' signals in the DS-CDMA environment. As noted earlier, the decision boundaries in a multi-user DS-CDMA communication environment are non-linear. In these cases, the neural network structures that include non-linear units are able to perform subtle non-linear boundaries in the signalling space to separate the wanted and unwanted signals.

The structure of this receiver is performed by using a bank of matched filters followed by a multi-layer perception unit, which is employed to transfer the output of the K matched filters into K data outputs. According to the adaptive nature of this receiver, the training sequences should be used for adjusting the interconnection weights of the receiver in a way to detect all users' signals in a multiple-access DS-CDMA channel. The MLP neural network receiver when used to implement a multi-user detector is trained on the basis of all the users' signature waveforms. In this situation, it needs to receive all users' signature waveforms during the training process and by changing the interconnection weights in its structure, establishes the boundaries needed to detect all users' data as a multi-user receiver.

5.6.8 The Recurrent Neural Network Receiver

The final multi-user receiver is the recurrent neural network receiver, which has been implemented in the simulation for the uplink DS-CDMA channel. This receiver uses a bank of matched filters followed by a recurrent neural network structure, the purpose of which is performed to transfer the output of K matched filters into K data outputs. The feedback links in the structure of the recurrent neural network enable it to store information about time in a dynamically stable configuration. For the case of symmetrical connection weights, if the network is started in any initial state, it will move towards a state where the energy function of the network reaches a minimum point and at this point, it stops changing with time. The energy function of the recurrent neural network can be properly determined via defining some suitable connection weights in the network. In the simulation, the energy function of the recurrent neural network is interpreted as the maximum-likelihood criterion. In this case, a multi-user receiver is realised, which minimises the distance metrics[5] in the multiple-access DS-CDMA environment.

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[5] The distance metrics has been explained in chapter two, equation (2-20).

5.7 Demodulation and Analysis of DS-CDMA Signals

The complex outputs from each of the receivers are demodulated with the appropriate level of phase-amplitude modulation prior to analysis. An analysis module, in the downlink channel, compares the suitably delayed transmitted data sequence of the desired user with the received sequence to produce statistics for the run including the bit error rate for all receiver types which have been simulated. In the uplink channel, the same task is done for all users in the multiple-access environment. In addition, the E_b/N_0 for the desired user is computed for each run from the simulation parameters. The software is also capable of monitoring the adaptive receiver's performance via mean-square error and adaptation algorithm convergence performance.

5.8   Summary

In this chapter, the structure of a DS-CDMA system, which has been simulated via a Monte-Carlo simulation technique by using Visual C^{++} software on the computer, has been described. It has been shown that, according to the location of the receiver in the channel, two different situations in the transmission channel are assumed. For the downlink channel, where the receiver is a mobile handset, the strategy is to design a single-user receiver that is able to despread the desired user's signal, reject the effect of co-channel interference and combat the effect of multipath channel. In this case, different receivers including the conventional matched filter receiver, the RAKE receiver, the adaptive MMSE receiver and the adaptive MLP neural network receiver have been implemented in the simulation. For the uplink channel, where the receiver is located in a base-station of a cell, the strategy is to design a multi-user receiver that is able to despread the signal of all co-channel users and minimises the effect of MAI on the detected data. In this case, the maximum-likelihood receiver, the decorrelating receiver, the adaptive MLP neural network receiver and the recurrent neural network receiver are implemented in the simulation. The performance evaluation of these receivers is the subject of the next chapter.

5.9 References

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Chapter Six

Performance Evaluation of DS-CDMA Receivers

6.1 Introduction

In this chapter, the performance of several receivers in the DS-CDMA communication system are evaluated via the Monte-Carlo simulation technique, which has been implemented by using visual C^{++} software on the computer. This evaluation includes the receivers for the downlink and the uplink mobile channels. In this way, two modes of data transmission, several models of the transmission channel, and different environments for signal reception are simulated. These options include synchronous and asynchronous modes of the data transmission, static and dynamic multipath channels, the power controlled and the 'Near-Far' environments. The objective of this chapter is to investigate the performance of the different types of receiver in the various channel model scenarios in a DS-CDMA multiple-access environment. The environment contains a number of co-channel users, where each user uses a unique signature waveform for data transmission, and the AWGN. In this situation, the main task of a DS-CDMA receiver is to combat the effect of strong MAI during detecting the transmitted data.

There are two different strategies in implementing the DS-CDMA receivers for the downlink and the uplink channels. For the downlink channel, to emphasise the privacy, the strategy is to use a single-user receiver to detect the desired user's signal and reject the other co-channel users' signal in the multipath mobile channel. In this case, each receiver uses its own unique signature waveform to detect the desired signal and reject other co-channel users' signal. In this situation, the performance of the conventional matched filter receiver, which is a classical receiver in the DS-CDMA system, is degraded with the strong co-channel users' signal. On the other hand, the RAKE receiver that is implemented to collect the distributed signal energy in the multipath DS-CDMA channel, does not function well in the 'Near-Far' multiple-access environment. It is shown that the adaptive MMSE receiver and the adaptive MLP neural network receiver have much better performance under different channel model scenarios and that they are suitable candidates to be used as a single-user receiver for the downlink DS-CDMA channel.

For the uplink channel, the strategy is to use a multi-user receiver, which detects all signals of the co-channel users in the multiple-access DS-CDMA environment. In this case, the best receiver with the highest performance is the maximum-likelihood receiver, which is known as the optimum multi-user receiver [6- 1]. In spite of good performance, unfortunately it requires a lot of additional information to operate in the DS-CDMA environment and its complexity grows exponentially with the number of co-channel users. These limitations make the maximum-likelihood receiver difficult to be implemented in a commercial environment. The

decorrelating receiver which is a multi-user receiver with implementation complexity that grows linearly with the number of users, requires to invert the correlation matrix of signature waveforms in the real time of data transmission to detect the data of all users. On the other hand, it does not use the amplitude information of the received signals to improve the performance of the receiver. It is shown here that the recurrent neural network receiver has attractive performance in the different channel model scenarios in the DS-CDMA environment, which is very similar to the performance of the optimum maximum-likelihood receiver. Also, its implementation complexity is much less than the implementation complexity of the maximum-likelihood receiver in a DS-CDMA environment, however it is still not linear. These features introduce the recurrent neural network receiver as a good alternative for maximum-likelihood receiver to be implemented as a multi-user receiver for the uplink channel in the multiple-access DS-CDMA environment.

The reminder of this chapter is organised as follows. In the following section the configuration of the system is explained. The third section evaluates the performance of the DS-CDMA receivers for the downlink channel and the performance of the DS-CDMA receivers for the uplink channel is considered in the fourth section. The summary comes in the final section.

6.2 System Configuration

The simulation software has been written to allow the DS-CDMA system to be investigated in a wide range of different channel model scenarios. In this way, different types of signature waveform, synchronous and asynchronous modes of data transmission, static and dynamic multipath of transmission channel and different environments for signal reception such as power controlled and 'Near-Far' environments have been simulated. The performance of several types of receivers in each part, has been obtained and compared with the performance of a benchmark receiver. The simulation specifications of the DS-CDMA system are shown in the Table 6. 1.

Carrier Frequency	900 MHz
Signature Waveform	ML, Gold codes and arbitrary
Signature Waveform Order, n	5 (31 Chips/Bit)
Maximum Number of Users	$2^n + 1$
Modulation	BPSK and DPSK
Timing Mode	Synchronous or Asynchronous
E_b/N_0	Variable

Table 6. 1: Simulated system specification.

6.3 Performance Evaluation of DS-CDMA Receivers in the Downlink Channel

For the downlink DS-CDMA channel, the receiver is a mobile handset that receives a signal from a base-station, which is located in the centre of a communication cell. The main task of the receiver is detecting the desired user's signal among other co-channel users, which are transmitting their signals simultaneously in the same band of frequency. In this case, a single-user strategy should be employed to perform the reception. The single-user receiver should be able to detect the desired user's signal and reject the MAI that is generated by other co-channel users. In addition, it should be able to combat the effect of multipath channel that is a main factor in decreasing the energy of the desired user's received signal.

6.3.1 Performance Evaluation of the Conventional Matched Filter Receiver

The simplest single-user receiver in a DS-CDMA system is the conventional matched filter receiver, which uses the desired user's signature waveform to detect the desired user data. The performance of this receiver depends on the characteristics of the signature waveform set, which has been employed to spread the data in the transmitter. In a single-user Gaussian channel, by using the maximum-likelihood criteria, the conventional matched filter receiver is the optimum receiver [6- 1]. In this case, the performance of this receiver represents the limit on the performance of receivers in the multi-user channel, when the MAI can be completely cancelled.

Figure 6. 1 shows the BER performance of the conventional matched filter receiver as a function of E_b/N_0 for a DS-CDMA single-user Gaussian channel. This result has been achieved by allocating a signature waveform with the length of 31chips/bit to the desired user. In this case, the processing gain of the direct sequence spread spectrum system is 31. This diagram shows the lower bound on the achievable BER performance of a 'Near-Far' resistance receiver in a multiple-access DS-CDMA channel with the processing gain of 31. Hence it can be used as a reference to evaluate the performance of the different MAI rejecting receivers.
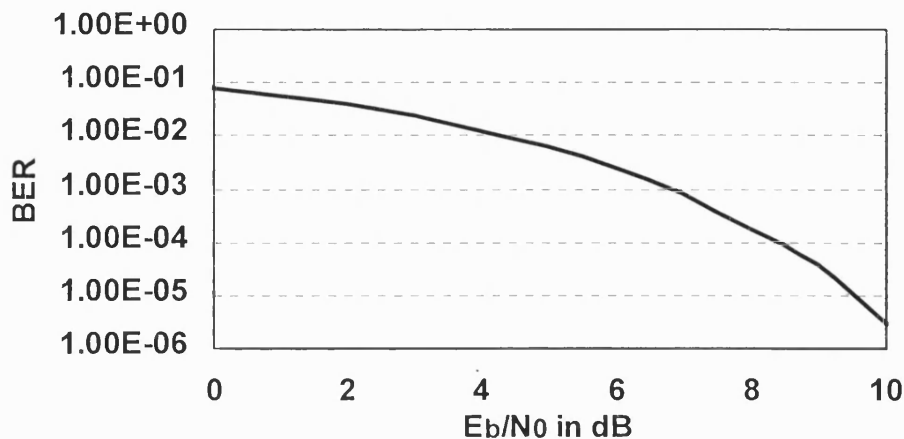
Figure 6. 1: The BER performance of the conventional matched filter receiver versus E_b/N_0 in a DS-CDMA single-user Gaussian channel.

In the ideal case, in a line-of-sight multiple-access DS-CDMA environment, if the signature waveform codes in the set are orthogonal, i.e. the cross-correlation values of different pairs of signature waveform are zero, the MAI will be removed from the channel. In this situation, the BER performance of the conventional matched filter receiver in the multiple-access channel will be the same as single-user channel. However in the real case, by using a suitable set of signature waveform to spread the data, such as the maximal length code or the Gold code, the values of cross-correlation of different users' signature waveform are not zero and hence the amount of MAI in the channel will be very limited. In this situation, with a synchronous mode of data transmission in a power-controlled and line-of-sight environment, the conventional matched filter receiver will have acceptable BER performance in the DS-CDMA system.

In a real DS-CDMA mobile environment and for the downlink channel, the power control techniques are very complicated and hence it is better to design the receiver to have a 'Near-Far' resistance property. The conventional matched filter receiver is a receiver, which has the

poorest resistance against the 'Near-Far' phenomena. Figure 6. 2 shows the weakness of this receiver to handle imperfect power control of the various users due to the 'Near-Far' effect in the DS-CDMA environment. In this case, the $E_{b(desired)}/N_0$ of the desired user's signal is set at 6dB whereas all of the co-channel interfering user's signals have an equal energy per bit, E_i. As it can be seen, the conventional matched filter receiver does not have good performance in this situation and the BER performance of this receiver degrades by increasing the energy of other co-channel user's signals. In other words, the resistance of the conventional matched filter receiver in the multiple-access 'Near-Far' DS-CDMA environment is very poor and it is not a suitable receiver for use in this channel.
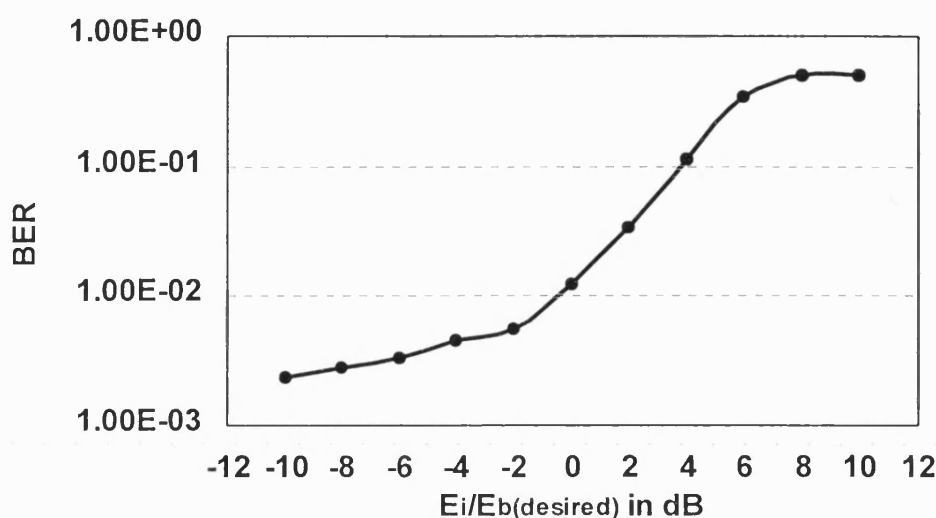
Figure 6. 2: The BER performance of the conventional matched filter receiver versus $E_i/E_{b(desired)}$ in a 10-user multiple-access 'Near-Far' DS-CDMA downlink channel.

The BER performance of the conventional matched filter receiver is also very sensitive to the number of co-channel interfering users. Figure 6. 3 shows the BER performance of this receiver as a function of the number of co-channel users in a multiple-access DS-CDMA environment. In this case, the $E_{b(desired)}/N_0$ of the desired user's signal is set to 6 dB whereas all of the other co-channel interfering user's signals have an equal energy per bit, E_i, where $E_i/E_{b(desired)}$ = 6 dB. In this case, a 'Near-Far' environment is simulated when the processing gain of the spread spectrum system is 31. It is clear that the BER performance of the conventional matched filter receiver degrades by increasing the number of co-channel user in the channel and in this case, the receiver completely loses its ability to detect the desired user's signal.

In summary, the performance of the conventional matched filter receiver in a multiple-access DS-CDMA environment is very sensitive to the amount of MAI, which is produced by the cross-correlation of the signature waveform pairs and is increased by the 'Near-Far' effect in the channel. In this case by increasing the power in the MAI, the BER performance of this receiver degrades. Several techniques such as better signature waveform design, using power control, using error correction codes and utilising adaptive antennas may be employed to reduce the amount of MAI and improve the performance of the conventional matched filter. However by using these techniques the complexity of the receiver is increased. It is clear, the conventional matched filter receiver is not suitable for use as a practical receiver in a mobile multiple-access DS-CDMA environment and a better strategy is to design 'Near-Far' resistance single-user receivers.
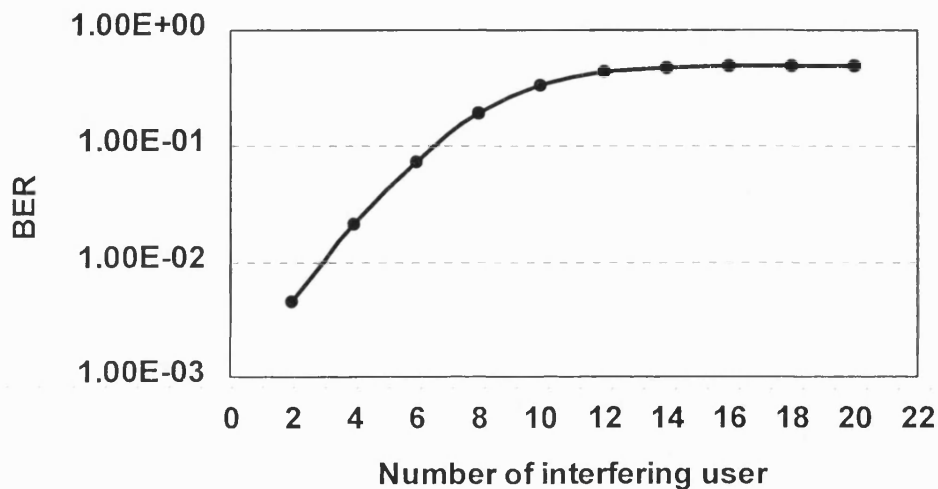
Figure 6. 3: The BER performance of the conventional matched filter receiver versus the number of co-channel interfering users in a 'Near-Far' multiple-access DS-CDMA channel.

6.3.2 *Performance Evaluation of the RAKE Receiver in a Multipath Channel*

In a real environment of the DS-CDMA data transmission system, the transmitted signal is received via different paths in the transmission channel. This phenomenon, which is called the multipath, is the effect of using high frequency carrier to carry the wide-band signal in the channel so that the wavelength of the carrier is small related to the scatters. In this case, the receiver receives different versions of the transmitted signal and it is required to employ a suitable receiver to combat this effect. In this situation, the RAKE receive, has been used to

collect the signals from each of the different paths. In order to implement the structure of the RAKE receiver, several information about the multipath channel should be provided. This information may be achieved by sounding the channel before starting to transmit the real data or during the real data transmission in the channel.

In a static multipath channel, where the transmitter and receiver are stationary, the characteristic of multipath channel should be estimated in the beginning of the real data transmission by sending known data into the channel and analysing the received data in the receiver. This technique is called 'sounding the channel' and is useful for determining the characteristic of the multipath channel. After sounding and achieving the delay profile and attenuation coefficients of the multipath channel, the RAKE receiver is implemented and the real data can be transmitted via the channel. Figure 6. 4 shows the BER performance of the RAKE receiver as a function of E_b/N_0 in a single-user static multipath DS-CDMA channel. The length of signature waveform is 31 chips/bit and in this case, the processing gain of the spread spectrum system is 31. The number of rays in the multipath channel is assumed to be six and also it is assumed that the delay profile and the attenuation coefficients of each ray in the multipath channel is known or has been determined in advance.
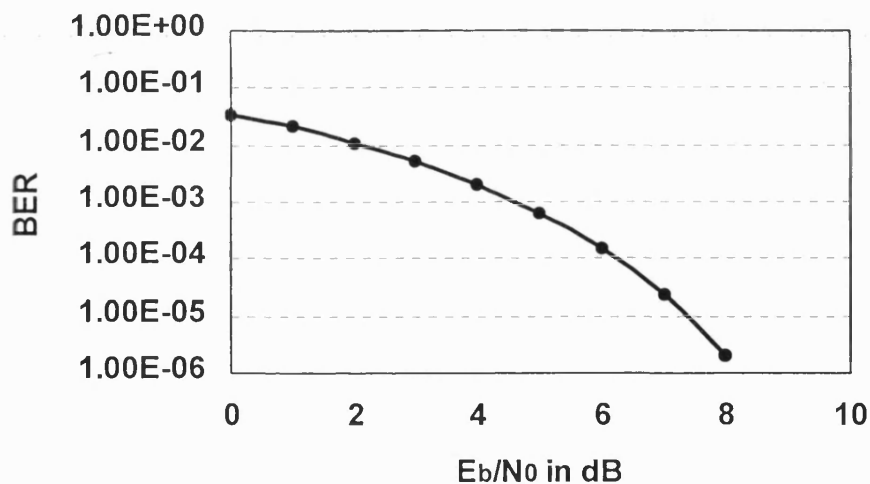
Figure 6. 4: The BER performance of the RAKE receiver versus E_b/N_0 in a six-ray static multipath DS-CDMA channel with known parameters.

It can be shown that in a single-user multipath channel by using the maximum-likelihood criteria, the RAKE receiver is the optimum receiver. In this case, the BER performance of this receiver is a reference that represents the limit on the BER performance of MAI rejecting

receivers in the multiple-access and multipath channel, when the MAI is completely cancelled. Hence this diagram is a good reference to compare the ability of the adaptive receivers for combating the effect of multipath in the DS-CDMA channel.

In a multipath-fading channel, where the transmitter and/or receiver are not stationary, the channel is a time varying system and its characteristic is changing during the real data transmission. In this case, it is needed to estimate the impulse response of the dynamic channel during real data transmission and employ it to implement the structure of the RAKE receiver to function in the time varying multipath channel.

In order to estimate the delay profile and attenuation coefficients of the dynamic multipath channel during real data transmission, usually two techniques are employed. These are the Maximal Ratio Combining (MRC) and the Equal Gain Combining (EGC) [6- 2]. These techniques use the post-correlation signal to estimate the multipath channel impulse response and the estimated parameters are updated by using a recursive filter during each bit interval. The only difference between the MRC and the EGC techniques is the model that is used for choosing the value of the weighting components of each tap[1]. It is shown that the estimated parameters, which are obtained in the multipath channel by using the MRC technique, are more accurate than the estimated parameters that have been achieved by using the EGC technique [6-2]. Actually, in the EGC technique, the estimator employs the sign of the post-correlation signals to perform the estimation, where in the MRC technique, the real value of the post-correlation signals are used in estimating process.

To verify the performance of the RAKE receiver in the dynamic multipath, a model of multipath-fading channel, which is called the COST207 model, is implemented in the simulation[2]. The channel model consists of a tapped-delay-line with six taps, which are spaced according to the GSM channel impulse response model. It is assumed that the carrier frequency is 900 MHz and the chip rate of the signal is 3.1×10^6 chips/sec and each delay space in channel model is approximately 0.2 μsec. The complex value of output from each tap is multiplied by a time varying Rayleigh distributed coefficient that characterises the fading channel. It is then multiplied by a further gain, which represents the average multipath signal strength expected at that delay. The weighting factors are chosen from the COST207 urban impulse response model, given in Table 6. 2.

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[1] The details of two MRC and EGC techniques are explained in Appendix B.

Path	1	2	3	4	5	6
Delay(μsec)	0.0	0.2	0.6	1.6	2.4	5
Gain(dB)	-3	0	-2	-6	-8	-10

Table 6. 2: The six-tap multipath-fading channel specification for the urban environment.

The outputs of all taps are then added together using a complex summer. The fast fading parameters are produced using six independent complex additive white Gaussian noise generators. The mobility of the user is incorporated into the channel by using the Doppler filters, which filter the Rayleigh distributed noise representing the path loss. For example, a 100 Hz Doppler frequency and a 900 MHz carrier frequency interprets as a vehicle speed of 120 km/h.

The BER performance of the RAKE receiver as a function of E_b/N_0 in the COST207 urban model of multipath-fading channel is shown in Figure 6. 5. The channel model contains six rays, where each follows by a Rayleigh distributed multiplying factor to generate the desired environment. To consider the effect of mobility of the receiver on the performance of the receiver, three different Doppler frequencies, which show the speed of the mobile receiver, have been implemented in the simulation. It is noted that the characteristic of multipath channel is estimated during the real data transmission and the MRC combining technique is employed to perform the RAKE receiver. It is shown that the RAKE receiver is able to recover the propagated signal in the single-user DS-CDMA multipath-fading channel. It is clear, by increasing the E_b/N_0 in the channel, the estimating error of the parameters in the dynamic channel is reduced. As it is shown, by increasing the Doppler frequency or increasing the speed of mobile unit, the BER performance of the RAKE receiver degrades. This degradation is the result of increasing the error in estimating the parameters of the dynamic channel.

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[2] The details of the COST207 model of multipath-fading channel are explained in Appendix B.
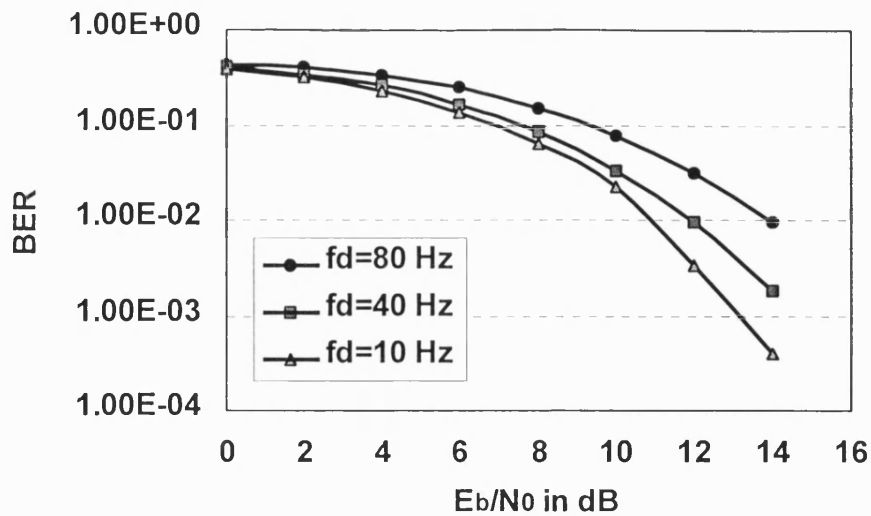
Figure 6. 5: The BER performance of the RAKE receiver versus E_b/N_0 in a COST207 Rayleigh multipath-fading single-user channel with different Doppler frequencies.

It is noted that the results in Figure 6. 5 are obtained in a single-user multipath-fading channel and the effect of MAI on the performance of the RAKE receiver is found to be identical to the conventional matched filter receiver. In this case as shown in Figure 6. 6, the BER performance of the RAKE receiver is degraded by MAI in the multiple-access DS-CDMA mobile channel. In this figure, the BER performance of the RAKE receiver as a function of E_b/N_0 in a multiple-access DS-CDMA multipath-fading channel is shown. It is assumed that the delay profile and attenuation coefficients of multipath channel are known and the Doppler frequency is 80 Hz. It can be seen that by increasing the number of co-channel interfering users, the BER performance of the RAKE receiver degrades until it has a very high irreducible BER. In a DS-CDMA multiple-access channel with 'Near-Far' effect, the BER performance of this receiver is worse than the power controlled environment. In this case, the strong signals of the co-channel interfering users overshadow the weak signal of the desired user and the RAKE receiver is unable to function properly in the multiple-access channel with 'Near-Far' effect.
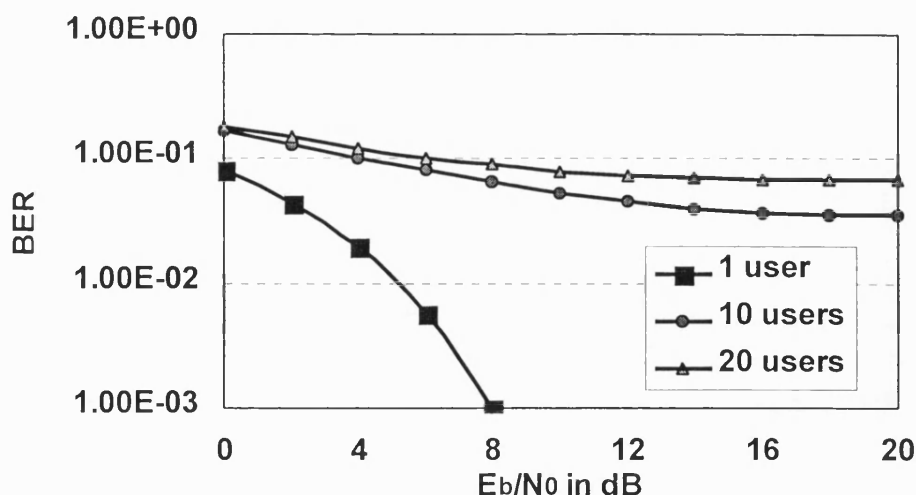
Figure 6. 6: The BER performance of the RAKE receiver versus E_b/N_0 in a power controlled multi-user DS-CDMA and a Rayleigh fading COST207 known multipath channel with f_d=80 Hz.

In summary, as considered in sections 6.3.1 and 6.3.2, the performance of the classic DS-CDMA receivers, such as the conventional matched filter receiver and the RAKE receiver, degrade because of MAI in the multiple-access environment and they are not able to combat the effect of MAI in these channels. A better strategy for implementing the DS-CDMA receiver, which is able to function in the multiple-access channel, is to use the adaptive structures. These structures can be employed to perform receivers to combat the effect of multipath and reject the effect of co-channel other user signals in the multi-user channels. In the next two sections, it will be shown that the performance of the adaptive receivers are far better than the performance of the classic receivers in the multiple-access DS-CDMA channel.

6.3.3 Performance Evaluation of the Adaptive MMSE Receiver

The adaptive MMSE receiver is a single-user receiver in DS-CDMA system, which can be employed to detect the desired user's signal in a multiple-access environment. As it has been shown in chapter three, where the mathematical basis of the adaptive MMSE receiver has been considered, it has the ability to be utilised as a conventional matched filter receiver in a single-user Gaussian channel or as a RAKE receiver in a single-user multipath channel. On the other hand, the adaptive nature of the receiver helps it to combat the effect of MAI in the multiple-access channel. In this section, the performance of the adaptive MMSE receiver is evaluated in

the different channel model scenarios via simulation. It is shown that this receiver has acceptable performance in these channel models and is suitable for use as a receiver in the DS-CDMA systems. The main structure of the adaptive MMSE receiver, the convergence performance, and the performance in the static and the dynamic multipath channel will be considered in this section.

6.3.3.1 The Main Structure of the Adaptive MMSE Receiver

In the DS-CDMA environment, after converting the received radio frequency signal to baseband, it is passed through a chip-matched filter. Then it is sampled at the end of every chip interval to provide input data for the adaptive part of the receiver. These samples are fed into the adaptive equaliser, which has been implemented by using a tapped-delay-line transversal structure. The output of the equaliser, in the simulation, is sampled once every bit interval, and passed through a hard limiter to generate an estimated data bit. The value of each tap weight in the transversal filter is updated once every bit interval and an error signal, which is the difference between the desired and the output signal of the adaptive filter, controls the updating process. This is done via a suitable adaptive algorithm, which has been employed to set the weight values of the adaptive receiver to the best point, where the value of error converges to zero. However in a practical system, the amount of error signal is not zero and there is always some residual error in the system. The value of the residual error in the system depends on several parameters, where the speed of convergence in the adaptive algorithm is one of them. In the adaptive systems with high-speed convergence property, the value of residual error is more than the low speed convergence systems. The effect of the step-size parameter in the adaptive algorithm on the speed of convergence and the value of the residual errors will be considered in the next section. Figure 6. 7 shows the main structure of the adaptive MMSE receiver.

In the simulation, which has been implemented, the structure of the adaptive MMSE receiver contains a delay line with 31 taps. In the beginning of the training mode, the value of all the weights in the structure, which are complex values, are set to zero. During training mode, these values are updating via an adaptive algorithm every bit interval to achieve a reasonable value of error in the system. After that, the updating process is stopped and the transmitter starts to send the real data. In the case of stationary channels, such as Gaussian or static multipath, the training sequences should be sent just in the beginning of the data transmission. To train the adaptive MMSE receiver, the known preamble data sequences for the desired user in the beginning of data transmission, are employed.
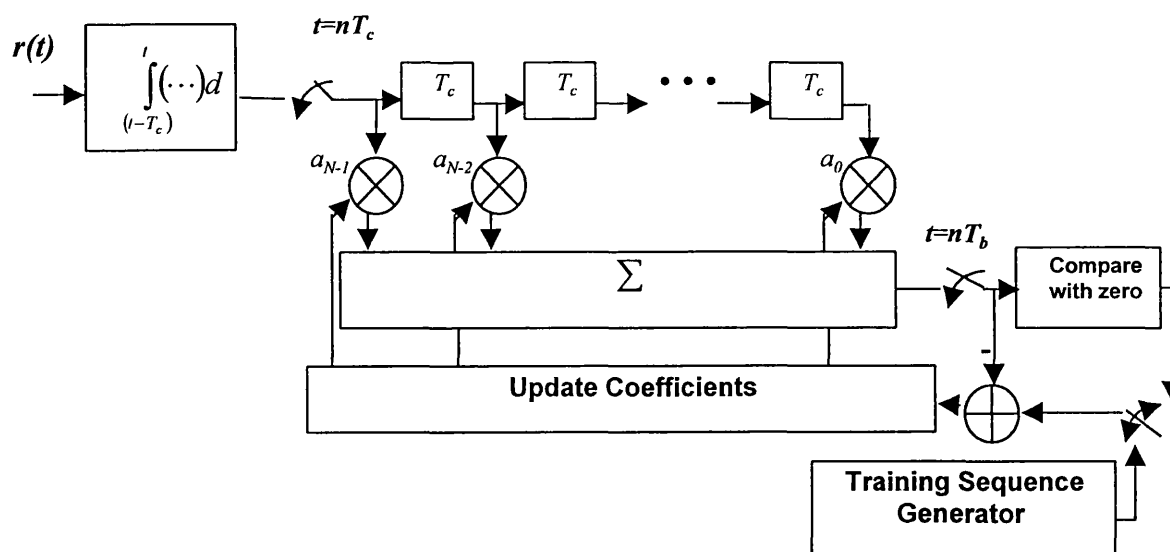
Figure 6. 7: The main structure of an adaptive MMSE receiver.

In dynamic channels, such as multipath-fading channels, the updating process will be continued during the real data transmission. In this case, the known midamble data sequences for the desired user, are employed regularly during real data transmission to maintain the value of error to an acceptable amount.

As the selected training sequences must be known at both the transmitter and the adaptive receiver, a suitable candidate in this case is the pseudorandom signature waveform of the desired user because it is a common information between the transmitter and the receiver in a DS-CDMA channel.

6.3.3.2 The Convergence Performance of the Adaptive MMSE Receiver

The amount of the mean square error in the adaptive algorithm is a measure that shows the convergence of the weight values of transversal filter to the desired values. In the ideal case and in a Gaussian DS-CDMA channel, the value of the weight vector will be equal to the signature waveform of the desired user, if the mean square error is zero. In practical systems, because of noise and other co-channel users' signal, there is some residual mean square error. In this case, the weight vector is maintained to the optimum position in the multi-dimensional space of weights.

The mean square error (MSE) convergence performances of the adaptive MMSE receiver in the different channel model scenarios are shown in Figure 6. 8, Figure 6. 9 and Figure 6. 10. In all of these cases, the energy of the desired user is set to achieve E_b/N_0 =15 dB in the channel and an LMS adaptive algorithm controls the value of the weight vector in a transversal filter with 31 taps. Also the step-size parameter of the adaptive algorithm has been set to μ =10^{-2}. The result in Figure 6. 8 has been achieved in a single-user environment, where the transmission channel only includes the desired user signal. It can be seen that convergence to a MSE of 0.2 (-7 dB) has been achieved after transmitting approximately 70 data bits or symbols.

In Figure 6. 9, the result has been achieved in a multi-user DS-CDMA channel, which contains five co-channel users. It is shown that in this case, convergence to a MSE of 0.2 (-7 dB) has been taken longer time than the single-user channel. By increasing the number of co-channel interfering users in the channel, as it is shown in Figure 6. 10, or increasing the energy per bit of the co-channel interfering users' signals, which shows the 'Near-Far' environment, the weight vector requires more time to converge to its optimum position to have minimum mean square error in the system.
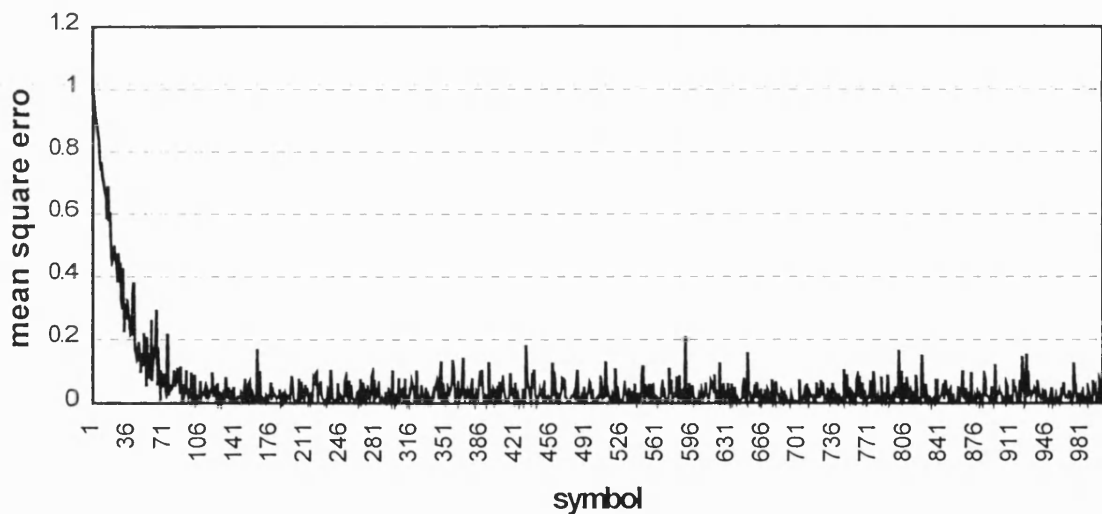
Figure 6. 8: The mean square error of the adaptive MMSE receiver in a single-user DS-CDMA channel.
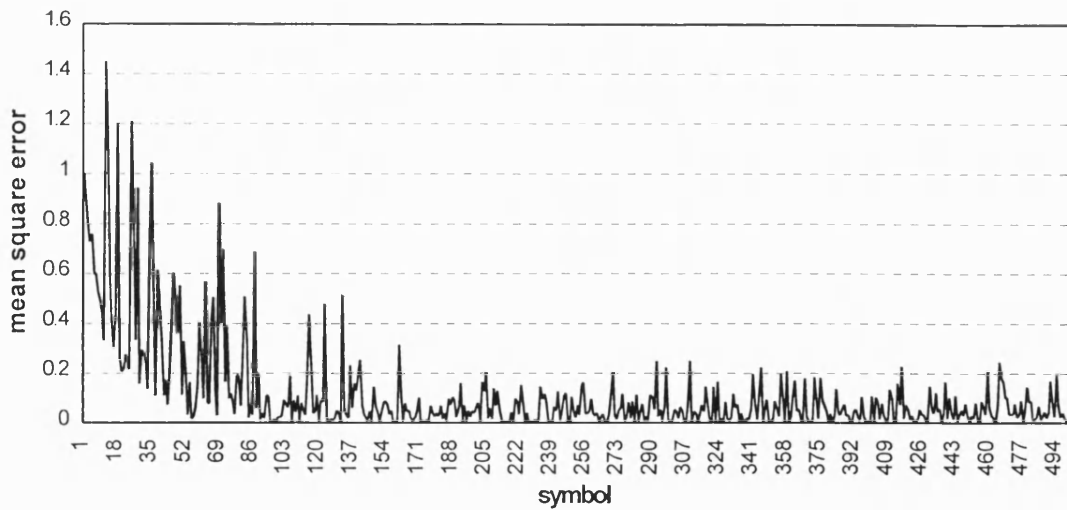
Figure 6. 9: The mean square error of the adaptive MMSE receiver in a 5-user multiple-access DS-CDMA channel.
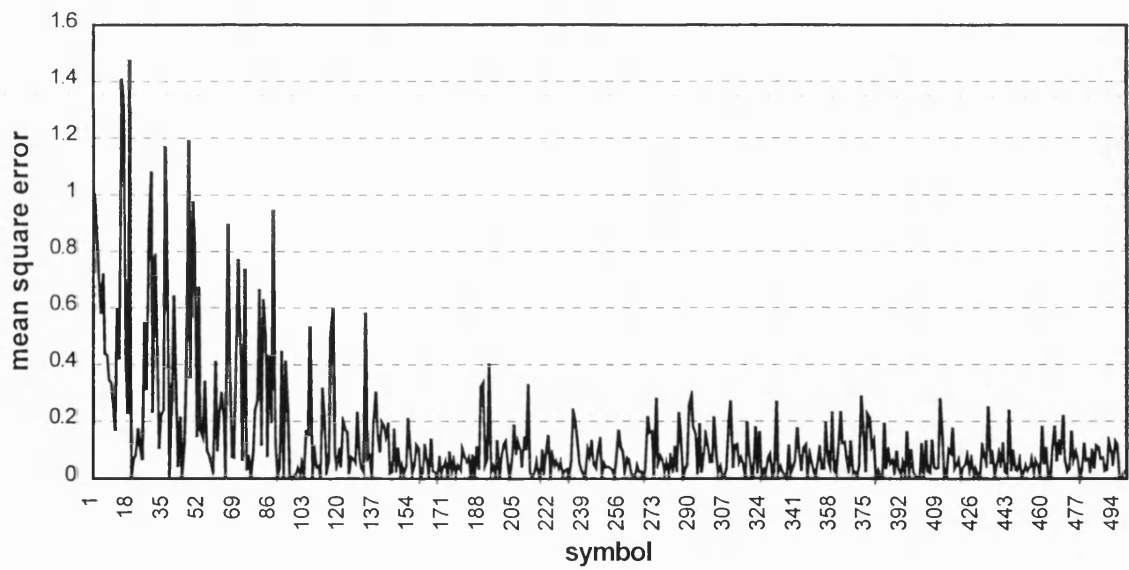
Figure 6. 10: The mean square error of the adaptive MMSE receiver in a 10-user multiple-access DS-CDMA channel.

Another factor, which has a large effect on the convergence performance of the adaptive systems, is the step-size parameter of the LMS algorithm. It controls the speed of the convergence process in the adaptive algorithm. However, by decreasing the step-size parameter, μ, the value of the mean square error decreases, but in this case the number of symbols, which are needed to be transmitted for achieving the desired MSE, increases. Figure 6. 11 and Figure 6. 12 show the convergence performance of the adaptive MMSE receiver in a single-user DS-CDMA system with different values of step-size parameter, μ. In Figure 6. 11, this parameter is set to $\mu = 10^{-1}$ and in Figure 6. 12, it is set to $\mu = 10^{-3}$. It can be seen that in the case of $\mu = 10^{-1}$, convergence to a MSE of 0.2 (-7 dB) has been achieved after transmitting approximately 30 data bits but in the case of $\mu=10^{-3}$, it has been achieved after transmitting approximately 700 data symbols. It is clear, by increasing the value of step-size, not only the speed of converging to the desired weight vector in the adaptive algorithm is increased but also the value of the residual error increases. In fact, for selecting the value of the step-size parameter in the adaptive algorithms, there is a compromise between the speed of convergence to the desired weight vector and the value of the residual mean square error in the system. It is clear that in the dynamic DS-CDMA channels, where the training sequences should be transmitted as midambles regularly during the real data transmission, using low speed adaptive algorithm is caused degradation in the performance of the adaptive receiver. In these conditions, it is better to accept some residual errors in the price of increasing the speed of adaptive algorithm.
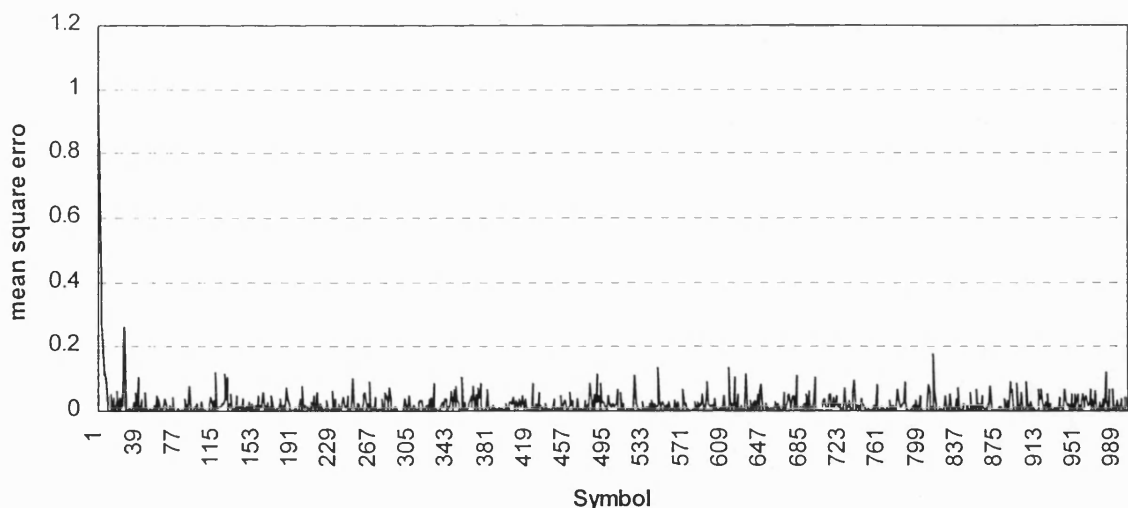
Figure 6. 11: The mean square error of the adaptive MMSE receiver with step-size value $\mu=10^{-1}$ in a single-user DS-CDMA channel.
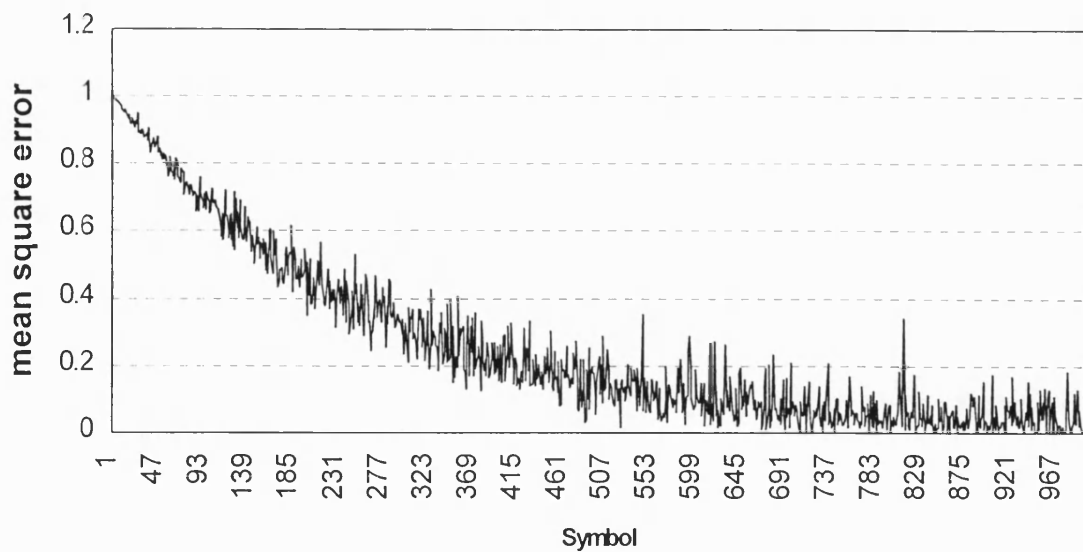
Figure 6. 12: The mean square error of the adaptive MMSE receiver with step-size value $\mu=10^{-3}$ in a single-user DS-CDMA channel.

6.3.3.3 Performance Evaluation of the Adaptive MMSE Receiver in a Multiple-Access DS-CDMA Channel

To evaluate the performance of the adaptive MMSE receiver in different channel model scenarios in the DS-CDMA environment, the bit error rate parameter has been chosen as a measure in the simulation. The BER is a good parameter, which can evaluate the performance of the adaptive MMSE receiver in different channel models, to combat the effect of noise and co-channel interfering other users signal and multipath.

The simplest model of a DS-CDMA channel is a Gaussian single-user environment, where the conventional matched filter receiver is the optimum maximum-likelihood receiver. The adaptive MMSE receiver has been implemented in this environment by using a transversal structure with 31 tap weights and LMS adaptive algorithm has been employed to change the weight vector. Also, a short known training sequence, in the beginning of the real data transmission, has been employed to set the weight vector of the adaptive receiver to detect the desired user's signal in the channel. In this case, the adaptive MMSE receiver had no information about the signature waveform of the desired user.

The BER performance of the adaptive MMSE receiver in a single-user DS-CDMA Gaussian channel is shown in Figure 6. 13. By comparing the BER performance in Figure 6. 13 and Figure 6. 1, which has been achieved in the same conditions for the conventional matched filter receiver, it can be seen that these results are completely identical.
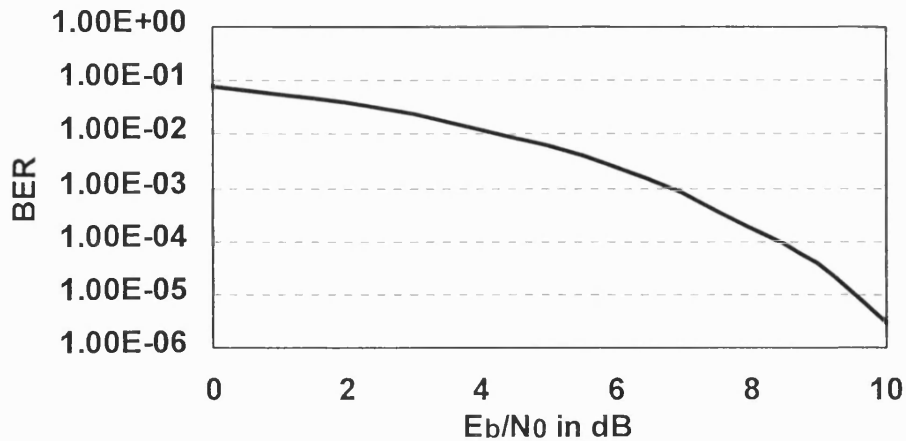
Figure 6. 13: The BER performance of the adaptive MMSE receiver versus E_b/N_0 in a single-user Gaussian DS-CDMA channel.

It means that the behaviour of the adaptive MMSE receiver in the single-user DS-CDMA channel is the same as the conventional matched filter receiver, which has the best performance in this environment. In this situation, the adaptive MMSE receiver via training process, learns to detect the desired user's signal and after converging the mean square error to its minimum level, the weight vector of adaptive receiver contains the signature waveform of the desired user. One advantage of the adaptive detectors is that they can set their weight vector in such way to receive another user's signal in the multi-user channel. In this case, by changing the training sequences the task performs and the adaptive algorithm set the weight vector to detect the new user's data.

In the multipath environments, the adaptive MMSE receiver, such as the RAKE receiver, should collect the different propagated rays of the desired user's signal in the channel to make a decision. In this case, the adaptive MMSE receiver via training process, learns the signature waveform of the desired user and the delay profile and attenuation coefficients of the multipath channel[3].

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[3] To use the RAKE receiver, the characteristic of multipath channel should be known or estimated via sounding the channel.

To evaluate the performance of the adaptive MMSE receiver in the multipath DS-CDMA channel, a static multipath channel with six rays has been implemented. The delay profile and attenuation coefficients have been set as the multipath channel specification for urban environment, which is shown in Table 6. 2. To compare the BER performance of the adaptive MMSE receiver, the RAKE receiver has been implemented in identical conditions. In the implementation of the RAKE receiver, it has been assumed that the delay profile and attenuation coefficients of the multipath channel are known. The adaptive MMSE receiver has been implemented by using a transversal structure with 31 tap weights and the LMS adaptive algorithm has been employed to set the weight vector. Also a short known training sequence, before beginning of real data transmission has been employed to set the weight vector of the receiver to detect the desired user's signal in the multipath channel. However the RAKE receiver has all information about the delay profile and attenuation coefficients of the multipath channel, but the adaptive MMSE receiver is only trained in the beginning of real data transmission. In this case, the adaptive MMSE receiver has no information about the signature waveform of the desired user and the characteristics of the multipath channel.

The BER performance of the adaptive MMSE receiver and the RAKE receiver as a function of E_b/N_0 is shown in Figure 6. 14. This result has been achieved in a single-user DS-CDMA and six-ray static multipath channel.
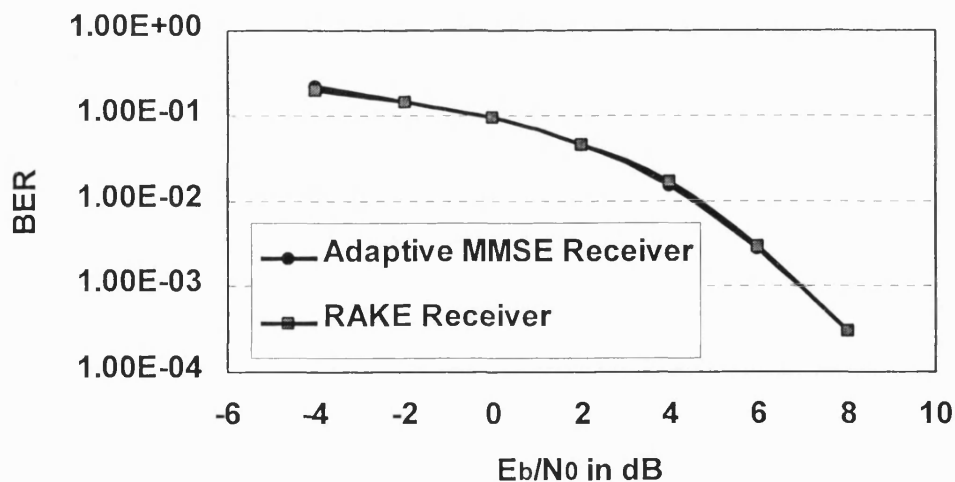
Figure 6. 14: The BER performance of the adaptive MMSE receiver and the RAKE receiver versus E_b/N_0 in a single-user DS-CDMA and a six-ray COST207 static multipath channel.

It can be seen that the adaptive MMSE receiver successfully detects the transmitted data and completely combats the effect of static multipath channel. The result shows that the BER performance of this receiver is identical to the BER performance of the RAKE receiver, which has the best performance in this environment. It is noted that the RAKE receiver has knowledge about the signature waveform of the desired user and the delay profile and attenuation coefficients of multipath channel whereas the MMSE receiver requires to achieve this information by itself in training mode. The perfect behaviour of the MMSE receiver to detect the desired user's signal in the multipath channel shows that this receiver can perform the maximum-likelihood criteria successfully in this environment.

As a DS-CDMA receiver, the MMSE receiver should combat the effect of other co-channel user interfering signals. In this way, for evaluating the BER performance of this receiver a multiple-access DS-CDMA channel has been simulated. The signature waveforms of all co-channel users have been chosen from a Gold code set with length 31 chips/bit. The asynchronous mode has been chosen for data transmission in the channel, where the delay of each user's signal is a random variable with uniform distribution between zero and 31. The E_b/N_0 of the desired user's signal has been set at 6 dB whereas all the co-channel interfering users' signals have an equal energy, which is 6 dB higher than the desired user's signal energy. The adaptive MMSE receiver has been implemented by using a transversal structure with 31 tap weights and a NLMS adaptive algorithm has been employed to set the weight vector. Also, the preamble sequences have been employed to train the receiver before the real data transmission. In this case, the receiver could set its weight vector to detect the desired user's signal in the multiple-access DS-CDMA channel.

To compare the BER performance of the adaptive MMSE receiver, a conventional matched filter receiver has been implemented in identical environment. To implement the conventional matched filter receiver, it has been assumed that the signature waveform of the desired user is known. Figure 6. 15 shows the BER performance of the adaptive MMSE receiver and the conventional matched filter receiver as a function of the number of co-channel user in the multiple-access DS-CDMA channel.

As can be seen, the performance of the adaptive MMSE receiver is substantially better than the performance of the conventional matched filter receiver. In this case, the BER performance of the conventional matched filter receiver is degraded by increasing the number of interfering users in the multiple-access DS-CDMA channel. On the other hand, the adaptive MMSE receiver sets its weight vector parameters via training to detect the desired user's signal and reject the co-channel interference signals. In this situation, it is apparent that the co-channel

interfering signals only increase the noise level in the channel. It is shown that the BER performance of the adaptive MMSE receiver is approximately constant by increasing the number of strong co-channel other users' signals. In this case, the receiver has good resistance against the MAI in the 'Near-Far' multiple-access DS-CDMA channel.
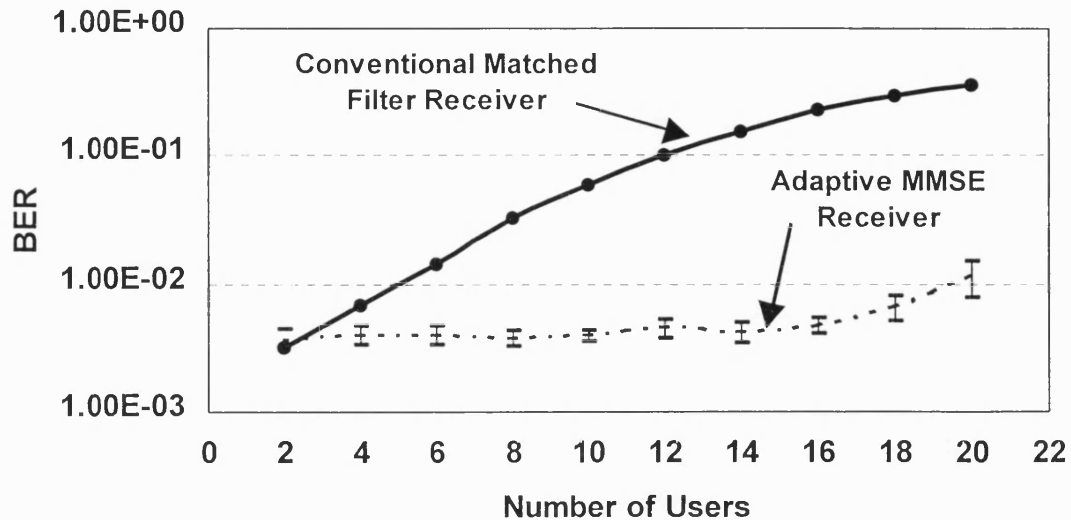
Figure 6. 15: The BER performance of the adaptive MMSE receiver and the conventional matched filter receiver versus the number of co-channel interfering user in a 'Near-Far' multiple-access DS-CDMA channel (the error bars show 95% confidence limits assuming normal distribution).

To evaluate the performance of the adaptive MMSE receiver in a 'Near-Far' environment, a DS-CDMA multiple-access channel with 10 co-channel interfering users has been simulated. The signature waveforms for all users have been chosen from a Gold code set with a length of 31 chips/bit. The asynchronous mode has been chosen for data transmission in the channel, where the delay value of each user's signal is a random variable with uniform distribution between zero and 31. The energy of the desired user has been set at $E_b/N_0 = 6$ dB and a 'Near-Far' environment has been assumed, where $E_i/E_{b(desired)}$ is varying in the channel . The adaptive MMSE receiver has been implemented by using a transversal structure with 31 tap weights and an NLMS adaptive algorithm has been employed to set the weight vector. Also preamble sequences for training the receiver has been used before starting to transmit the real data in the channel. In this case, the receiver could set its weight vector to detect the desired user's signal in the multiple-access DS-CDMA channel. To compare the BER performance, the conventional matched filter receiver has been implemented in identical environment.

Figure 6. 15 shows the BER performance of two receivers as a function of E_i /$E_{b(desired)}$ in the DS-CDMA channel, which includes strong co-channel interference signals. As is predicted, the performance of the adaptive MMSE receiver is substantially better than the performance of the conventional matched filter receiver. In this case, the BER performance of the conventional matched filter receiver degrades by increasing the energy of co-channel interference signals in the DS-CDMA channel. On the other hand, the BER performance of the adaptive MMSE receiver is not very sensitive to the energy of co-channel interfering users' signals and it is approximately constant when the energy of co-channel interfering user's signals are varying in a wide range.
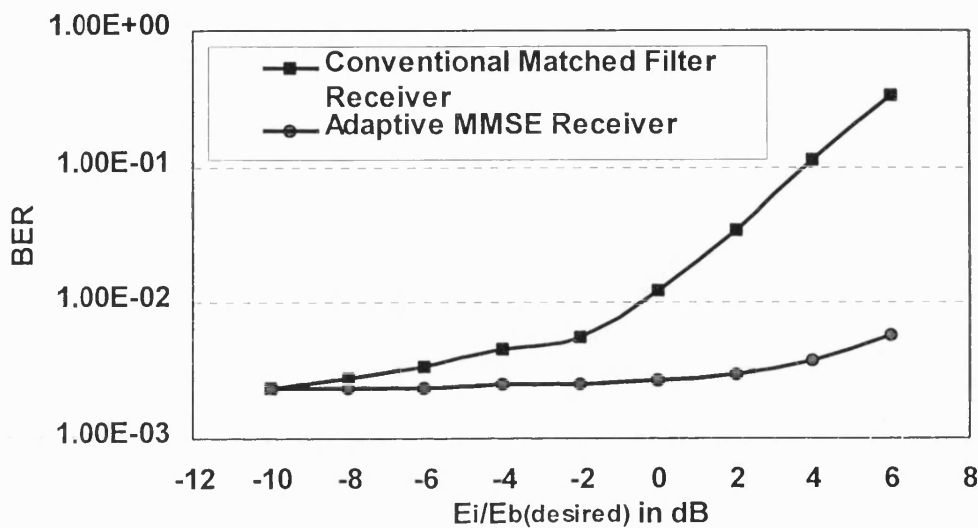
Figure 6. 16: The BER performance of the adaptive MMSE receiver and the conventional matched filter receiver versus $E_i/E_{b(desired)}$ in a 'Near-Far' multiple-access DS-CDMA channel.

It is noted that the result has been obtained for a low amount of E_b/N_0, where the adaptive MMSE receiver must set its weight vector to detect the weak desired user's signal in the channel that includes strong co-channel interfering user's signals and high level AWGN. If the level of the E_b/N_0 is increased in the channel, the BER performance of the adaptive MMSE receiver will be improved in the 'Near-Far' DS-CDMA environment.

6.3.3.4 Performance Evaluation of the Adaptive MMSE Receiver in a Static Multipath Channel

To evaluate the BER performance of the adaptive MMSE receiver in the multipath channel, a 10-user multiple-access DS-CDMA and a six-ray static multipath channel have been implemented. The signature waveforms of all co-channel users have been chosen from a Gold code set with length 31 chips/bit. The asynchronous mode has been chosen for data transmission in the channel, where the delay of each user's signal is a random variable with uniform distribution between zero and 31. The received signal's energy per bit is identical for all users and in this case a power-controlled environment has been assumed. The adaptive MMSE receiver has been implemented by using a transversal structure with 31 tap weights and an NLMS adaptive algorithm has been employed to set the weight vector. Also a preamble sequence for training the receiver has been used before starting to transmit the real data in channel. In this case, the receiver could set its weight vector to detect the desired user's signal in the multiple-access and multipath channel. To compare the BER performance, the RAKE receiver has been implemented in an identical environment. It has been assumed that the RAKE receiver has all information about delay profile and attenuation coefficients in the multipath channel.

Figure 6. 17 shows the BER performance of two receivers as a function of E_b/N_0 in the static multipath DS-CDMA channel, which includes co-channel interference signals.
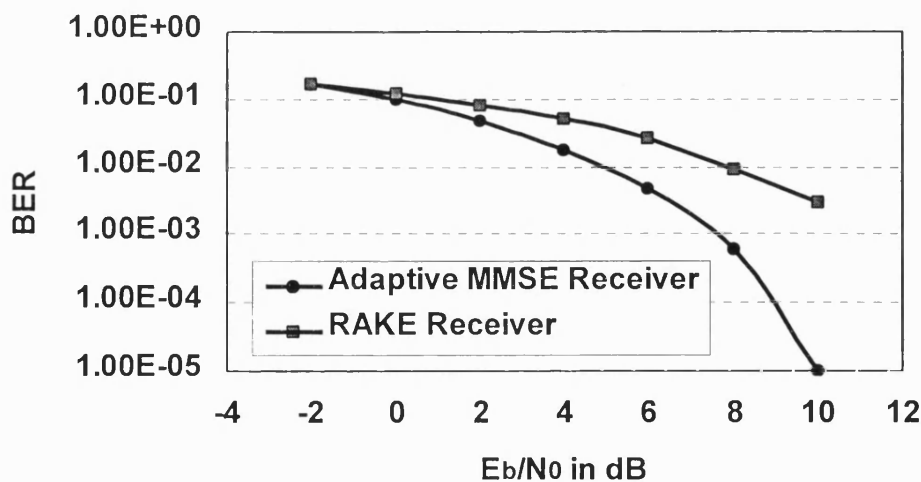
Figure 6. 17: The BER performance of the adaptive MMSE receiver and the RAKE receiver versus E_b/N_0 in a power controlled 10-user multiple-access DS-CDMA and a six-ray COST207 static multipath channel.

As can be seen, the adaptive MMSE receiver successfully detects the transmitted data in the multi-user DS-CDMA channel and thus completely combats the effect of the static multipath. In this case, the adaptive receiver is successful in despreading the desired user's signal, combating the effect of multipath channel and rejecting co-channel interfering users' signals. The MAI in the channel causes degradation in the BER performance of the RAKE receiver and in this case, it does not function well as a receiver in a multi-user DS-CDMA environment.

In summary, the result of this section has shown that the adaptive MMSE receiver can be implemented in the multiple-access DS-CDMA environment to detect the desired user's data and reject the MAI. It has been shown that the weight vector of this receiver in a single-user Gaussian channel, via the training process, converges to the signature waveform of the desired user. In this case, the BER performance of the adaptive MMSE receiver is found to be identical to the BER performance of the conventional matched filter receiver, which has the best performance. In a multipath single-user DS-CDMA channel, where the RAKE receiver has the best performance, the adaptive MMSE receiver has the potential to be implemented as the RAKE receiver. In this case, the BER performances of these receivers are found to be identical. The 'Near-Far' resistance of the adaptive MMSE receiver in the multiple-access DS-CDMA environment is the most important advantage of this receiver. It is shown that the adaptive MMSE receiver is able to detect the desired user's signal between strong co-channel interference signals. In a multi-user DS-CDMA environment, where the desired user's signal is propagated via different rays in the multipath channel, the adaptive MMSE receiver despreads the desired user's data, combats the effect of multipath and rejects the co-channel interference from the other user signals.

6.3.3.5 Performance Evaluation of the Modified Adaptive MMSE Receiver in a Multipath-fading Mobile Channel

As considered in chapter three, the performance of the adaptive MMSE receiver degrades in the multipath-fading DS-CDMA channel, where the mobility of the receiver causes the adaptive algorithm to lose the phase lock of the desired signal. In the fading channels with slow Doppler frequency, the adaptive MMSE receiver can track the phase parameter of the desired user's signal, but by increasing the Doppler frequency, the phase lock will be lost. In this case, the value of the mean square error in the adaptive algorithm is increased and the adaptive MMSE receiver loses its ability to track and detect the desired user's data. In this situation, an equaliser is needed to remove the effect of time varying multipath-fading channel on the received signal before entering the MMSE filter.

The novel modified adaptive MMSE receiver that has been introduced in chapter three, is able to function in the multipath-fading and multi-user DS-CDMA environment. In this case, an equaliser is maintained in front of the adaptive MMSE receiver to help it for combating the effect of multipath-fading channel. The equaliser uses the estimated parameters of the time varying channel to compensate the effect of multipath on the received signal. In this case, the output signal of the equaliser contains the desired user's data and MAI, where the adaptive part of the receiver can detect the desired user's signal and reject the MAI.

To verify the ability of the modified adaptive MMSE receiver to combat the effect of the multipath-fading channel and reject the MAI, the adaptive receiver of Figure 6. 18 has been implemented in the simulation.
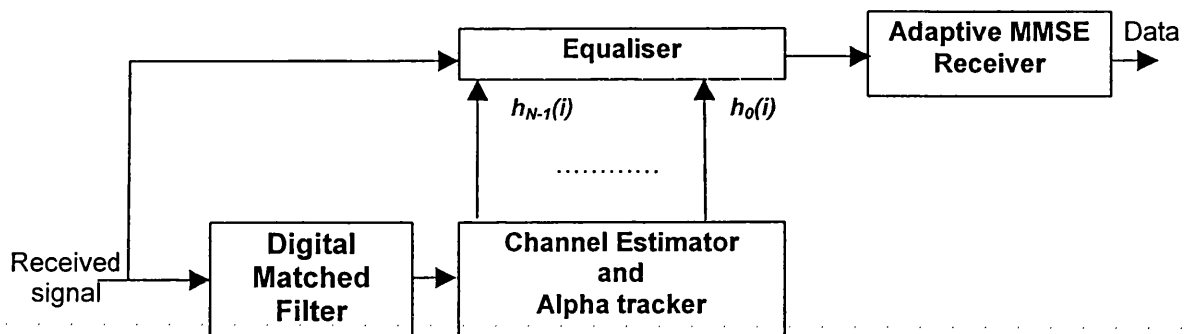
Figure 6. 18: The structure of modified adaptive MMSE receiver.

By using the complex NLMS algorithm, the 31 complex tap weights of the adaptive receiver have been set during training process and real data sequence transmission. To prevent losing the phase lock on the desired user's signal in the adaptive algorithm and increasing the BER in the receiver, the known midamble sequences have been sent during real data transmission. The spreading waveform sequence for all co-channel users have been chosen from a Gold code set of length 31 chips and DPSK modulation scheme has been used in the DS-CDMA channel. The asynchronous transmission mode has been assumed in the simulation and the relative clock offset, τ_k, for all of users have been chosen randomly from a uniform distribution. To compare the BER performance of the modified adaptive MMSE receiver, the RAKE receiver has been also simulated under identical conditions.

The dynamic COST207 multipath-fading environment has been implemented in the simulation of channel[4]. The channel model consists of a tapped-delay-line with six taps, which are spaced according to the GSM channel impulse response model. It is assumed that the carrier frequency is 900 MHz and the chip rate of the signal is 3.1×10^6 chips/sec and each delay space in the channel model is approximately 0.2 μsec. The complex value of output from each tap is multiplied by a time varying Rayleigh distributed coefficient that characterises the fading channel. It is then multiplied by a further gain, which represents the average multipath signal strength expected at that delay. The weighting factors are chosen from the COST207 urban impulse response model, given in Table 6. 2. The outputs of all taps are then added together using a complex summer. The fast fading parameters are produced using six independent complex additive white Gaussian noise generators. The mobility of the user is incorporated into the channel using Doppler filters, which filter the Rayleigh distributed noise representing the path loss. For example a 100 Hz Doppler frequency and a 900 MHz carrier frequency interprets a vehicle speed of 120 km/h.

Figure 6. 19 shows the BER performance of the modified adaptive MMSE receiver and the RAKE receiver as a function of E_b/N_0 in a single-user Rayleigh multipath-fading channel with 80 Hz Doppler frequency.

Figure 6. 19: The BER performance of the modified adaptive MMSE receiver and the RAKE receiver versus E_b/N_0 in a six-ray COS207 Rayleigh multipath-fading single-user DS-CDMA channel.

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[4] The details of the COST207 model of multipath-fading channel are explained in Appendix B.

In this case, it is assumed that the delay profile and the attenuation coefficients of the dynamic multipath channel are known. As can be seen, there is no significant difference between the BER performances of the modified adaptive MMSE receiver and the RAKE receiver, which has the best performance in this environment.

Figure 6. 20 and Figure 6. 21, respectively, show the BER performance of the RAKE receiver and the modified adaptive MMSE receivers as a function of E_b/N_0 in the multipath-fading channel with 80 Hz Doppler frequency. It is assumed that the delay profile and the attenuation coefficients of the multipath channel are known. The DS-CDMA channel includes the co-channel interfering user signals, where a power-controlled condition is assumed. It can be seen that the modified adaptive MMSE receiver has an excellent performance for combating the effect of MAI in the multipath-fading channel.
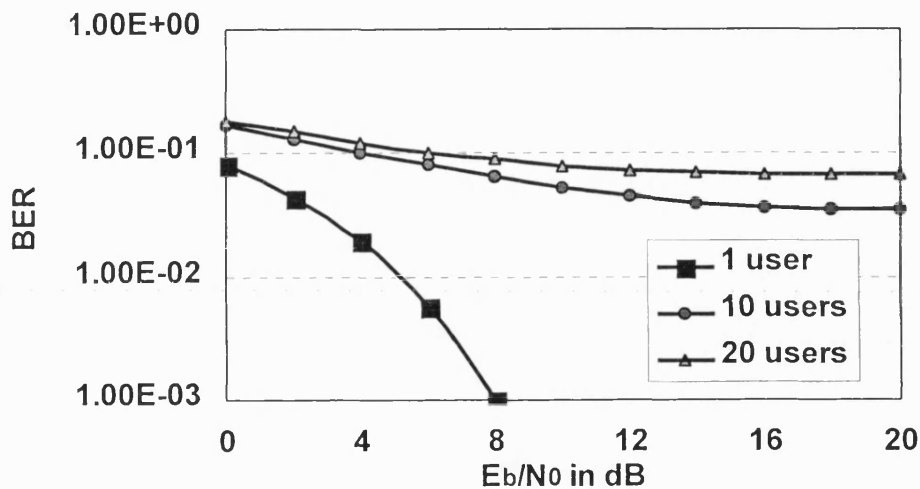
Figure 6. 20: The BER performance of the RAKE receiver versus E_b/N_0 in a six-ray COST207 Rayleigh multipath-fading and multiple-access interference DS-CDMA channel.
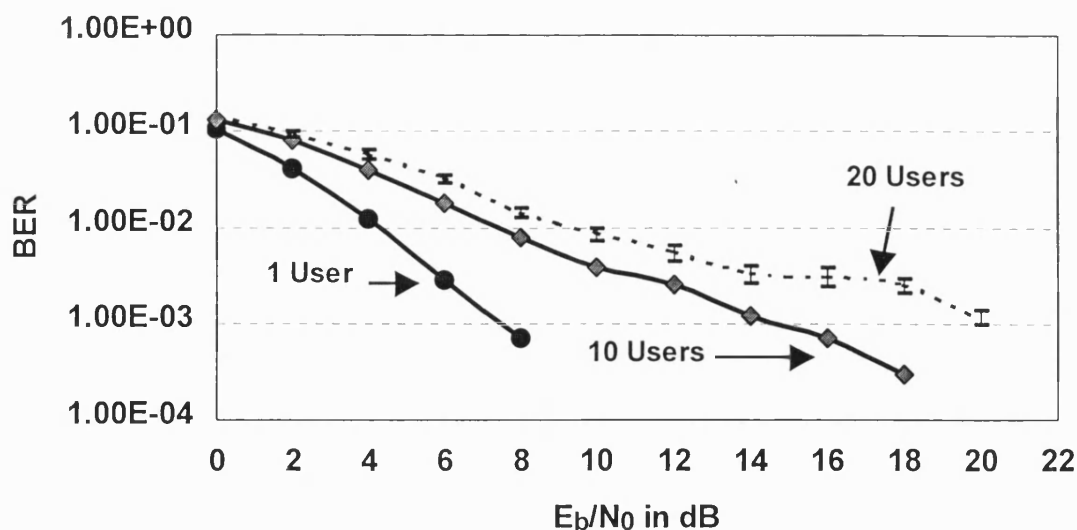
Figure 6. 21: The BER performance of the modified adaptive MMSE receiver versus E_b/N_0 in a six-ray COST207 Rayleigh multipath-fading and multiple-access interference DS-CDMA channel (the error bars show 95% confidence limits assuming normal distribution).

In a realistic case, it is necessary to estimate the delay profile and attenuation coefficients of the time varying multipath channel and to employ the estimated parameters to equalise the effect of the multipath channel on the received signal. To estimate the channel's parameters, the MRC technique [6- 2] has been used in the simulation. In this case, by using the complex conjugate of the estimated parameters of the channel's parameters, the equaliser has been performed.

Figure 6. 22 shows the BER performance of the modified adaptive MMSE receiver versus E_b/N_0 in a six-ray COST207 Rayleigh fading channel. In this case, the MRC technique has been employed to estimate the delay profile and attenuation coefficients of the multipath channel. To investigate the BER performance of adaptive system in various speeds of receiver in the DS-CDMA multipath channel, different Doppler frequencies have been considered in the simulation.
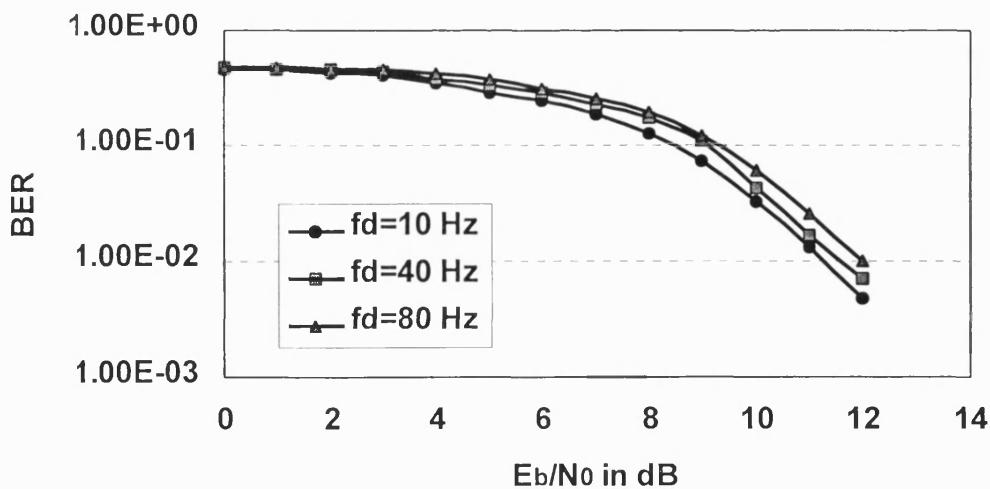
Figure 6. 22: The BER performance of the adaptive modified MMSE receiver versus E_b/N_0 in a six-ray COST207 Rayleigh multipath-fading single-user DS-CDMA channel.

It can be seen that the adaptive MMSE receiver has an acceptable BER performance in this situation. It is noted that in higher E_b/N_0, the performance of the modified adaptive MMSE receiver is far better than the lower E_b/N_0. This is because, in higher E_b/N_0, the error of estimating the multipath channel delay profile and attenuation coefficients, is small and the equaliser is more successful at removing the effect of the multipath channel on the received signal.

Figure 6. 23 shows the BER performance of the modified adaptive MMSE receiver as a function of E_b/N_0 for different numbers of co-channel interfering users. The result has been achieved for a six-ray COST207 Rayleigh multipath-fading environment, where the MRC technique is employed to estimate the delay profile and attenuation coefficients of channel. It is observed that by increasing the number of co-channel interfering users, the noise level in the DS-CDMA channel increases and hence the BER performance of the adaptive receiver degrades. It is clear that by increasing the E_b/N_0, the estimation of multipath channel parameters will be more accurate and in this case, the BER performance of the adaptive receiver is improved. In the other words, the BER performance of the modified adaptive MMSE receiver is far better in higher E_b/N_0 and it is because of better estimating of the multipath-fading channel characterises.
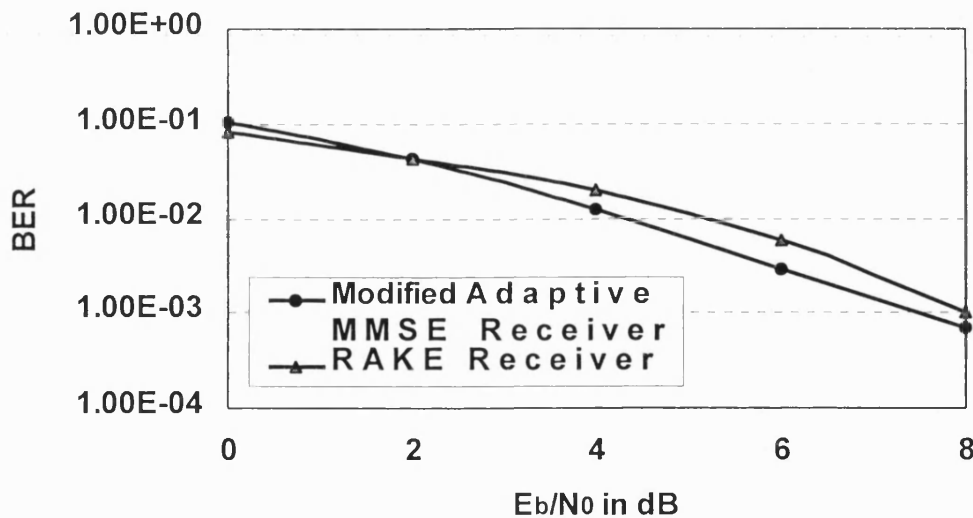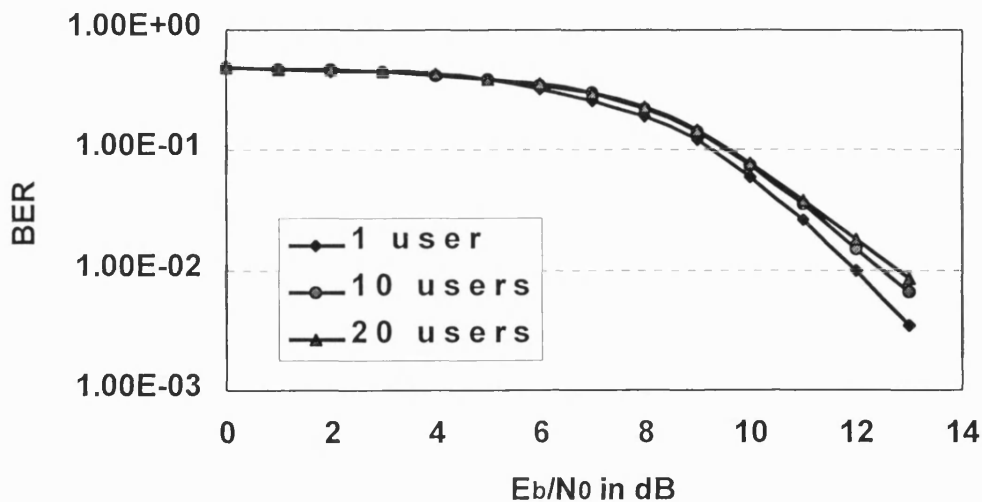
Figure 6. 23: The BER performance of the modified adaptive MMSE receiver versus E_b/N_0 in a six-ray COST207 Rayleigh multipath-fading and multiple-access interference DS-CDMA channel.

In summary, the modified adaptive MMSE receiver is a suitable receiver in the DS-CDMA multipath-fading channel. In a time varying multipath channel, where the adaptive part of the receiver may lose the phase lock on the desired user's signal, the equaliser compensates the effect of time varying channel on the received signal. In this case, the signal at the output of equaliser includes the desired user's signal plus MAI, where the adaptive part of the receiver can detect wanted signal and reject unwanted signal.

The BER performance of the modified adaptive MMSE receiver in the multipath-fading channel mostly depends on the quality of estimating the channel characteristics. To estimate the delay profile and attenuation coefficients of multipath-fading channel, the Maximal Ratio Combining (MRC) is employed, which is known as a good estimation technique in the DS-CDMA environment. The result shows that the modified adaptive MMSE is a suitable receiver for rejecting the MAI in the multipath-fading mobile channels.

6.3.4 Performance Evaluation of the Adaptive MLP Neural Network Receiver

The adaptive MLP neural network receiver can be used as a single-user receiver for a DS-CDMA system. It is trained to detect the desired user's signal, which is defined as a wanted pattern, and also to reject the co-channel other users' signal as unwanted patterns in the multiple-access environment. As shown in chapter four, where the adaptive MLP neural network has been considered, it has the potential to be implemented as a DS-CDMA receiver in a multiple-access environment. On the other hand, it can be trained in a multipath environment to function as a RAKE receiver to detect the desired user's signal, which has been received via different rays in a DS-CDMA channel. The adaptive nature of the MLP neural network receiver helps it to perform subtle boundaries between the wanted and unwanted signals in the multiple-access DS-CDMA environment and hence combats the effect of MAI in the multiple-access channel. In this section, the performance of the adaptive MLP neural network receiver is evaluated for different channel model scenarios via computer simulation. It is shown that this receiver has acceptable performance in these conditions and is a suitable receiver that can be employed as a single-user receiver in the DS-CDMA systems. The performance of the adaptive MLP neural network receiver in different DS-CDMA environments is considered in this section.

6.3.4.1 The Convergence Performance of the Adaptive MLP Neural Network

The value of sum square error (SSE) in applying back-propagation adaptive algorithm, is a parameter that determines the convergence of the interconnection weights of the MLP neural network to the desired values. The zero value for this parameter shows that the MLP neural network performs successfully the subtle boundaries between the wanted and unwanted signals. In the practical systems, because of noise and co-channel users' signals, there is always some residual sum square errors.

As it has been shown in chapter four, the learning rate or step-size parameter in back-propagation algorithm is a parameter that determines the convergence rate of the adaptive algorithm of an adaptive MLP neural network system. Figure 6. 24 shows the SSE, which have been achieved when simulating a multi-layers feedforward neural network.
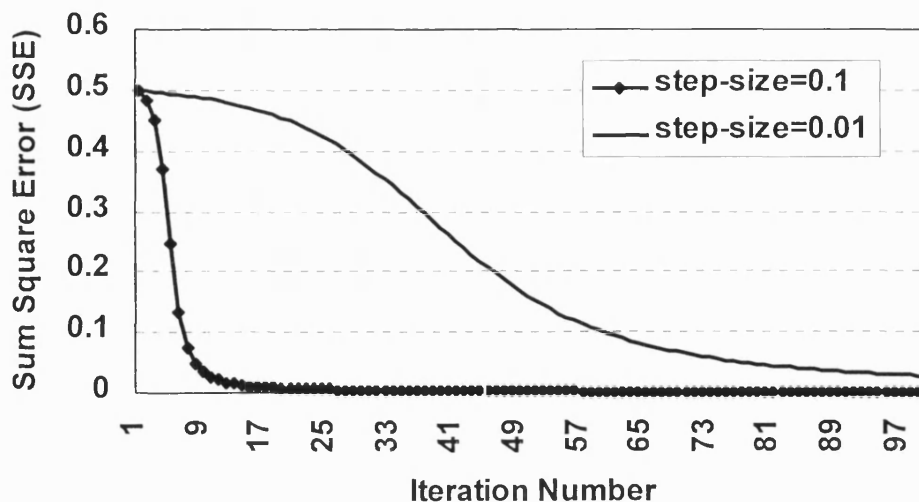
Figure 6. 24: The Sum Square Error (SSE) of a typical multi-layer perceptron neural network during learning mode.

The simulated MLP neural network includes 31 nodes in the input layer, 15 nodes in the hidden layer and one node in the output layer of its structure. As can be seen, by allocating a small value for the step-size parameter, the system requires more iterations of the training sequence to achieve the minimum level of SSE. In this case, the value of the residual SSE is very small. On the other hand, by increasing the value of the step-size parameter, the speed of convergence is increased and after a few iterations of training sequence, the sum square error decreases to an acceptable value. In this case, the system may have larger amount of residual SSE. If the step-size parameter is chosen too large to speed up the rate of learning process in the adaptive algorithm, the network may become unstable.

6.3.4.2 The Number of Nodes in the Hidden Layer of a MLP Neural Network

To verify the ability of the adaptive MLP neural network structures as a single-user DS-CDMA receiver, a multi-layer neural network with three layers has been simulated. These layers are called the input, the hidden and the output layers respectively. The input layer includes 31 nodes, which is equal to the number of chips in the signature waveform that are employed to spread the data in the spread spectrum DS-CDMA channel. The number of nodes in the output layer is one node, where the desired user's data appears.

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To determine the number of nodes in the hidden layer[5], which are sufficient for our application, a three-layer perceptron receiver in a 10-users DS-CDMA multiple-access environment has been simulated. The back-propagation algorithm has been employed to set the interconnection weights of the neural network during learning process. The spreading sequences for all users in the channel have been chosen from a Gold code set of length 31 chips/bit. Also BPSK modulation is used for all users' data. The relative clock offset, τ_k, of all users are assumed to be zero to simulate the synchronous mode of operation. The energy per bit of the desired user's signal, which has been set to obtain $E_b/N_0 = 6$ dB, is 6 dB less than the energy per bit of other co-channel users' signals that shows a 'Near-Far' environment.

Figure 6. 25 shows the BER performance of the adaptive MLP neural network receiver as a function of the number of nodes in the hidden layer.
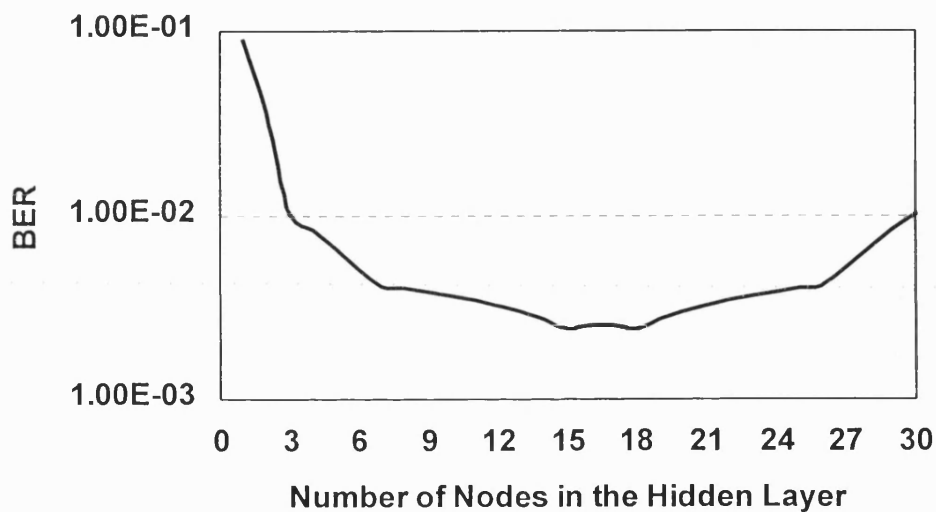
Figure 6. 25: The BER performance of the adaptive MLP neural network receiver versus the number of nodes in the hidden layer in a 10-user 'Near-Far' multiple-access DS-CDMA channel.

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[5] As it is noted in chapter four, determining the number of nodes in the hidden layer of MLP neural network sufficient for a given task, is an open problem and depends on the nature of pattern classification tasks.

As is shown, by using a few nodes in the hidden layer, the structure of the receiver is simple but its BER performance is not good. In this case, the receiver is unable to distinguish between the wanted and unwanted signals in the channel. By increasing the number of nodes in the hidden layer, the complexity of the neural network receiver increases and also the BER performance of the adaptive MLP neural network receiver is improved. This process is continued till 15 nodes in the hidden layer and after that the BER performance of the receiver remains constant for a small range of increasing the number of nodes in the hidden layer. Further increases in the number of nodes in the hidden layer, the BER performance of the receiver degrades. This result shows that increasing the number of nodes in the hidden layer does not always improve the BER performance of receiver.

According to the results of the simulation, the number of nodes in the hidden layer of the adaptive MLP neural network receiver has been chosen to be 15 nodes. In this case, the best and reliable performance with a low implementation complexity is achieved in the simulation of the receiver, which is also acceptable in this application.

6.3.4.3 Performance Evaluation of the Adaptive MLP Neural Network Receiver in a Multiple-Access DS-CDMA Channel

To evaluate the performance of the adaptive MLP neural network receiver as a single-user receiver in a multiple-access DS-CDMA environment, this receiver with 31 nodes in the input layer, 15 nodes in the hidden layer and one node in the output layer has been implemented. The back-propagation algorithm has been employed during learning mode with transmitting the known data. To compare the BER performance, the conventional matched filter receiver has been implemented under identical conditions.

The BER performance characteristics of the adaptive MLP neural network receiver and the conventional matched filter receiver in the multi-user DS-CDMA channel are shown in Figure 6. 26. The channel includes 10 co-channel users, where the energy per bit of each interfering user's signal is 6 dB more than the energy per bit of the desired user's signal. This represents unequal power control or the 'Near-Far' environment in the DS-CDMA channel. It can be seen that the adaptive MLP neural network receiver outperforms the conventional matched filter receiver in the presence of strong multiple-access interfering user signals. In this situation, it has an acceptable performance for combating the effect of strong MAI.

Figure 6. 26: The BER performance of the adaptive MLP neural network receiver and the conventional matched filter receiver versus E_b/N_0 in a 10-user 'Near-Far' multiple-access DS-CDMA channel.

To verify the 'Near-Far' resistance of the adaptive MLP neural network receiver, a multiple-access DS-CDMA environment with 10 co-channel users has been implemented. In this situation, the energy per bit of the desired user's signal is set to obtain E_b/N_0 = 6 dB and the effect of unequal received power for each co-channel interfering user, simulating the 'Near-Far' effect, is also considered. Figure 6. 27 shows the BER performance of two receivers as a function of $E_r/E_{b(desired)}$ in the multiple-access DS-CDMA channel. In this situation, the ability of the adaptive MLP neural network receiver to reject the effect of co-channel interfering signals under a wide range of changing bit energy is far better than the conventional matched filter receiver.

In Figure 6. 28, the effect of increasing the number of co-channel user on the BER performance of two receivers is shown for both the adaptive MLP neural network receiver and the conventional matched filter receiver. The conditions are identical in both cases and represent a multi-user interference channel that includes different number of co-channel interfering user with a 6 dB 'Near-Far' situation. It can be seen that the adaptive MLP neural network receiver outperforms the conventional matched filter receiver in rejecting the multiple access interference. The BER performance of the adaptive MLP neural network receiver, by increasing the number of co-channel users, is approximately constant whereas the BER performance of the conventional matched filter receiver degrades as the number of co-channel users increases.

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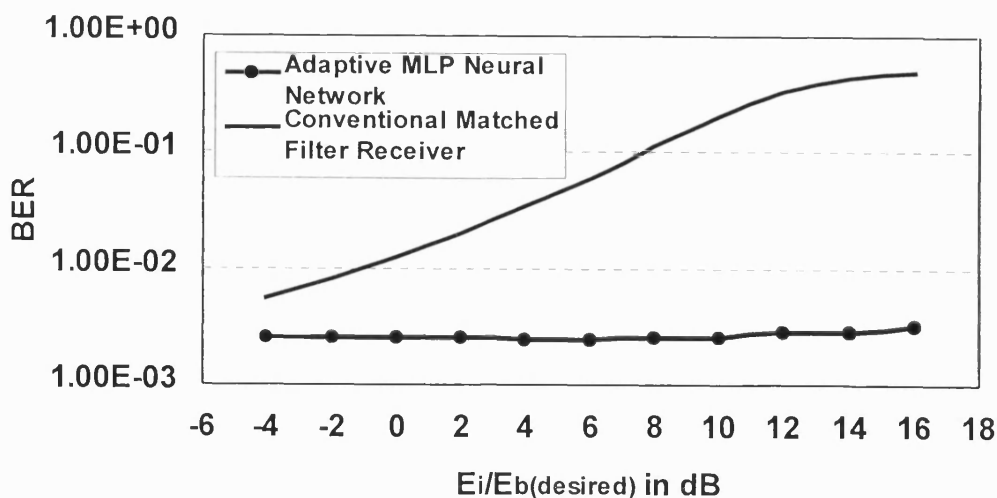
Figure 6. 27: The BER performance of the adaptive MLP neural network receiver and the conventional matched filter receiver versus $E_i/E_{b(desired)}$ in a 10-user multiple-access 'Near-Far' DS-CDMA channel.
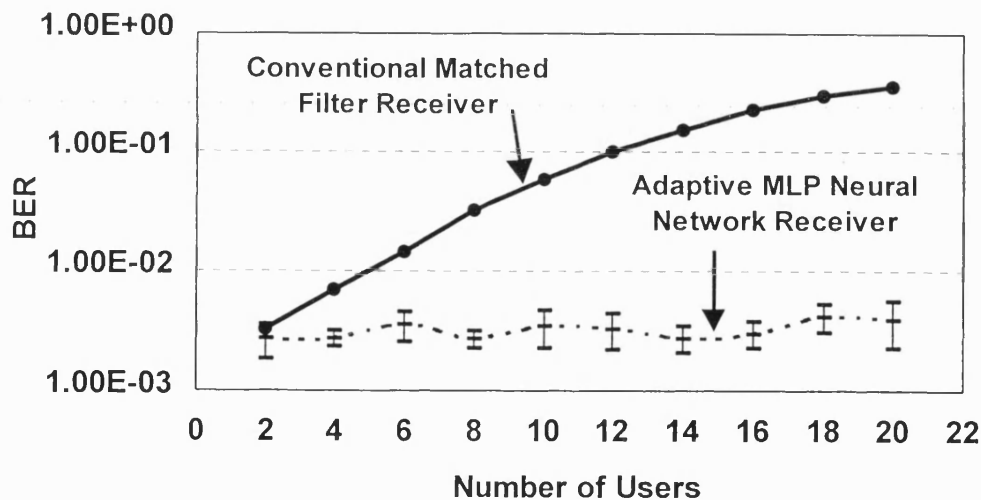
Figure 6. 28: The BER performance of the adaptive MLP neural network receiver and the conventional matched filter receiver versus the number of co-channel user in a 'Near-Far' multiple-access DS-CDMA channel (the error bars show 95% confidence limits assuming normal distribution).

In summary, the adaptive MLP neural network receiver has the potential to be used as a single-user DS-CDMA receiver in the multiple-access environment. In this way, subtle boundaries can be performed, via the learning process, to separate the desired user's signature waveform as the wanted and the co-channel interfering user's signature waveforms as the unwanted signals. It has been shown that the adaptive MLP neural network receiver, as a single-use receiver, has excellent 'Near-Far' resistance in the multiple-access DS-CDMA channel.

6.3.4.4 Performance Evaluation of the Adaptive MLP Neural Network Receiver in a Static Multipath DS-CDMA Channel

To evaluate the performance of the adaptive MLP neural network receiver in the multiple-access DS-CDMA and multipath channel, a DS-CDMA multiple-access and a six-ray static multipath channel with ten co-channel interfering users has been implemented. The signature waveforms of all users have been chosen from a Gold code set with length 31 chips/bit. The energies of all co-channel user signals are identical and in this case a power-controlled environment has been assumed. The adaptive MLP neural network receiver has been implemented by using three-layer structure and a back-propagation algorithm has been employed to set the interconnection weights during training mode. In this case, the received signals via different rays in the multipath channel have been introduced as the wanted signals for the receiver. To compare the BER performance, the RAKE receiver has been implemented in identical environment.

Figure 6. 29 shows the sum squared error of the adaptive MLP neural network receiver in the training mode in a 10-user multiple-access and a 6-ray static multipath DS-CDMA channel. In the back-propagation training algorithm, which has been emploed, the step-size parameter, α, is equal to 0.1.

It is assumed that the adaptive MLP neural network receiver has information about the signature waveform of all co-channel users and the delay profile of multipath channel. It can be seen that in this case, the sum square error converges to its minimum level after approximately 120 iterations.
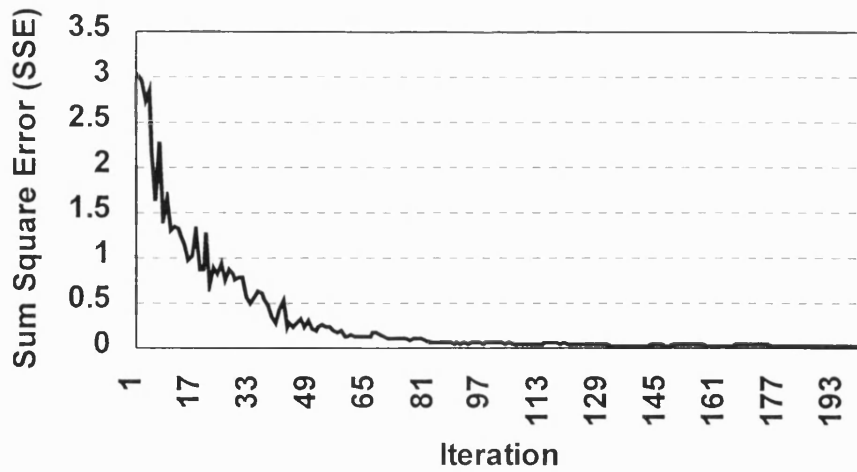
Figure 6. 29: Sum Square Error (SSE) of the adaptive MLP neural network receiver in a 10-user multiple-access DS-CDMA and a six-ray COST207 multipath channel.

Figure 6. 30 shows the BER performance of the adaptive MLP neural network receiver and the RAKE receiver, which have been achieved in a 10-user multiple-access DS-CDMA and a 6-ray multipath channel. The energy per bit of each interfering user is 6 dB more than the energy per bit of the desired user, which simulates the 'Near-Far' environment in transmission channel.

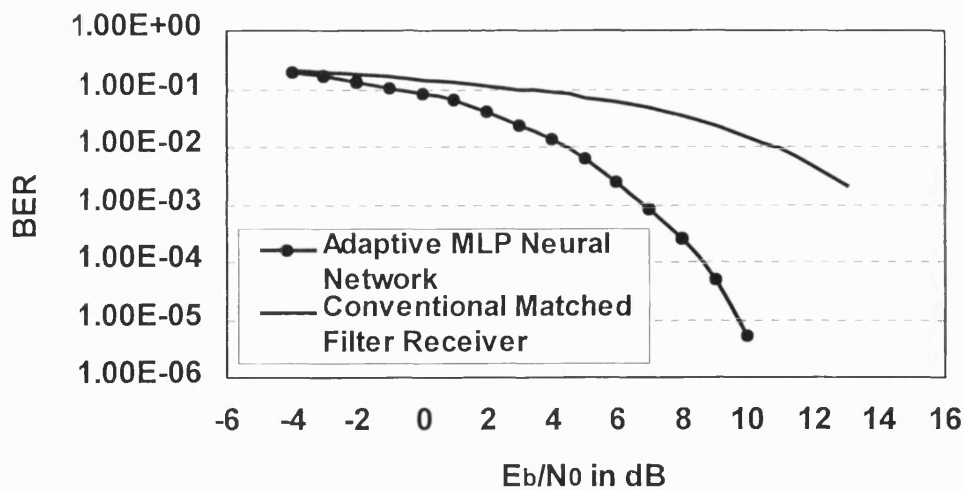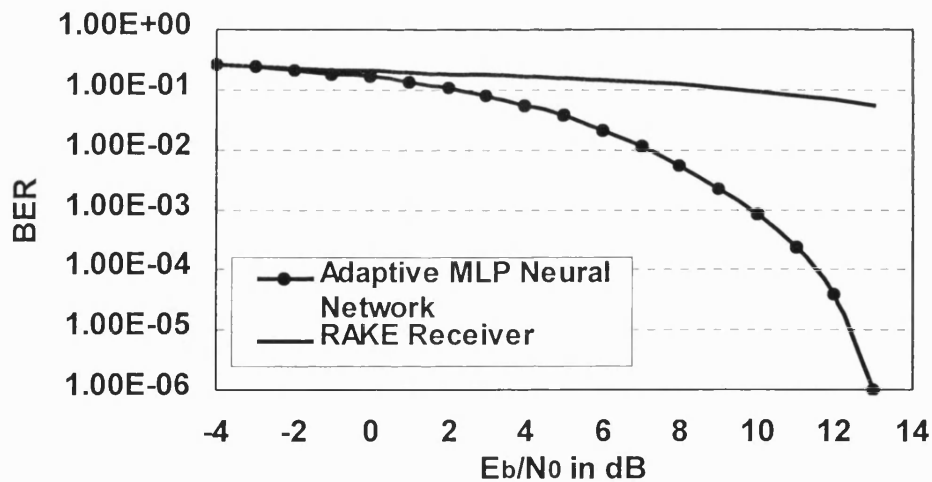**Figure 6. 30: The BER performance of the adaptive MLP neural network receiver and the RAKE receiver versus E_b/N_0 in a 10-user 'Near-Far' multiple-access DS-CDMA and a six-ray COST207 multipath channel.**

It is shown that the BER performance of the adaptive MLP neural network receiver is far better that the BER performance of the RAKE receiver, in identical environment. In fact in this situation, the adaptive MLP neural network receiver performs three functions. The first, as a matched filter to despread the desired user signal. The second, as a RAKE receiver to collect the propagated energy of the desired signal, which have been propagated in different rays of the multipath channel. The third, as an interference-rejecting receiver to reject the co-channel interfering users in a 'Near-Far' environment.

6.3.4.5 Performance Evaluation of the Adaptive MLP Neural Network Receiver in a Multipath-Fading Channel

In this section, the performance of the adaptive MLP neural network receiver in multipath-fading channel with different Doppler frequencies is investigated. The fast fading parameters of the multipath channel have been produced using six independent complex additive white Gaussian noise generators. The mobility of the user incorporated into the channel through the Doppler frequency of the Rayleigh fading statistics. The Doppler effect is added by shaping the AWGN using a classical Doppler filter[6]. To investigate the performance of the adaptive MLP neural network receiver in the Rayleigh multipath-fading, a 6-ray time varying multipath channel with Rayleigh distribution for the amplitude and uniform distribution for the phase of each ray in different Doppler frequencies has been implemented. In this situation, a complex back-propagation algorithm [6- 3], [6- 4] is employed to set the interconnection weights and the threshold levels of neurones in the different layers of the receiver. The multiple-access DS-CDMA channel includes 10 co-channel interfering users and a power-controlled environment has been assumed.

Figure 6. 31 shows the BER performance of the adaptive MLP neural network receiver as a function of E_b/N_0 in the Rayleigh multipath-fading with different Doppler frequencies. It is shown that in the static multipath channel, where the Doppler frequency is zero, the receiver has a good ability to function in this environment. By increasing the mobility of the receiver in the channel, the BER performance of the adaptive MLP neural network receiver is degraded. In this case, the receiver has acceptable BER performance in the low rate Doppler frequencies up to 20 Hz. This value of Doppler frequency may be generated in the channel when the receiver is moving with speed of 30 km/h. The BER performance of the adaptive MLP neural network receiver is not enough good in the higher rate of Doppler frequencies. In these cases, this

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[6] It will be explain in Appendix B.

receiver is not successful to detect the desired user's signal and reject co-channel interfering user signals. This result can be interpreted as the adaptive MLP neural network receiver is suitable to be employed for vehicles with slow motion speed or walking people in the mobile DS-CDMA environments. The military environment is an example of these situations.
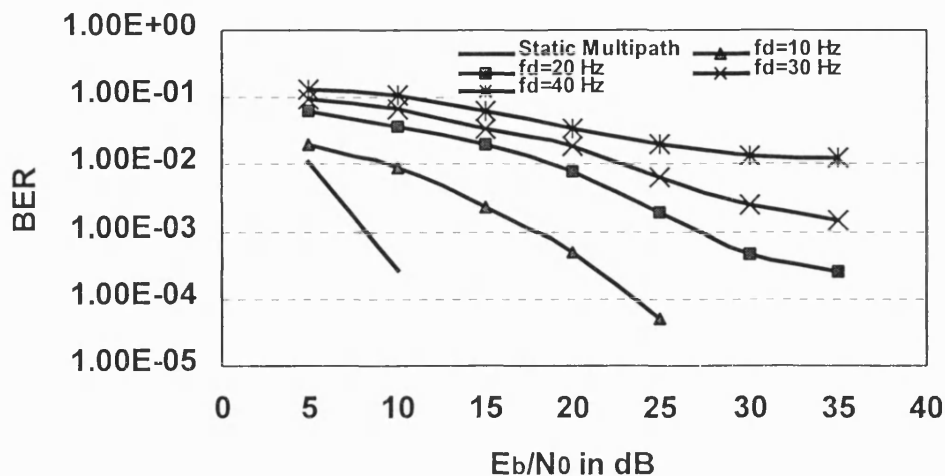
Figure 6. 31: The BER performance of the adaptive MLP neural network receiver versus E_b/N_0 in a six-ray COST207 Rayleigh multipath-fading channel with different Doppler frequencies and a 10-user multiple-access DS-CDMA environment.

In the two recent sections, the performance of the adaptive MLP neural network receiver, as a single-user receiver in the multipath DS-CDMA environment, is investigated via simulation. It has been shown that in the static multipath channel, the adaptive MLP neural network receiver through training process learns to collect different rays of propagated signal of the desired user in the channel. However the ability of this receiver for rejecting the co-channel interfering users' signals in the Rayleigh multipath-fading channel decreases by increasing the Doppler frequency, but it has acceptable performance in the low rate time varying multipath-fading and multiple-access channels.

6.3.5 Performance Comparison of the Adaptive MMSE and the Adaptive MLP Neural Network Receivers

It has been considered that the adaptive receivers are potentially good candidates to be implemented as a single-user receiver in the DS-CDMA environment. The adaptive MMSE and the adaptive MLP neural network are two receivers that can be employed for this application.

It has been shown that the performance of the adaptive MMSE receiver is acceptable in the different channel model scenarios. It can be employed as a conventional matched filter receiver to despread the received signal without any knowledge about the signature waveform of the desired user in the Gussian channel. It can be implemented as a RAKE receiver to collect different rays of propagated energy in the multipath channel without any information about the delay profile and attenuation coefficients of the channel. It has the ability to reject the strong co-channel interfering users' signal in the 'Near-Far' multiple-access DS-CDMA environment. The modified adaptive MMSE receiver is able to function as a single-user receiver in the Rayleigh multipath-fading channel.

On the other hand, the adaptive MLP neural network receiver has acceptable performance as a single-user receiver in the DS-CDMA environment. It can be employed to despread the desired user's signal and reject the MAI in the multiple-access DS-CDMA channel. It is also can collect the different rays of the propagated energy in the multipath channel. The performance of this receiver is acceptable in the slow rate of multipath-fading channel.

To compare the performance of the adaptive MMSE and the adaptive MLP receivers in different channel model scenarios, a DS-CDMA multiple-access channel with ten co-channel interfering users has been implemented. The signature waveforms of all users have been chosen from a Gold code set with length 31 chips/bit. Also BPSK modulation is used for all users' data. The relative clock offset, τ_k, of all users are assumed to be zero to simulate the synchronous mode of operation. The energy per bit of each co-channel interfering user signal is 6 dB higher than the energy per bit of the desired user's signal. In this case, a 'Near-Far' DS-CDMA environment has been assumed.

The adaptive MMSE receiver has been implemented by using a transversal structure with 31 tap weights and a NLMS adaptive algorithm has been employed to set the weight vector. Also preamble sequence for training the receiver has been used before transmitting the real data. In this case, the receiver could set its weight vector to detect the desired user's signal in the

multiple-access channel. The adaptive MLP neural network receiver has been implemented by using three-layer MLP structure and a back-propagation algorithm has been employed during the training mode to set the interconnection weights.

Figure 6. 32 shows the BER performances of two receivers as a function of E_b/N_0 in a DS-CDMA channel, which includes strong co-channel interference signals. As it can be seen, the adaptive MMSE and the adaptive MLP neural network receivers successfully detect the transmitted data and reject MAI in the 'Near-Far' multi-user DS-CDMA channel. In this case, the BER performances of two receivers are found to be approximately identical.

Figure 6. 32: The BER performance of the adaptive MMSE receiver and the adaptive MLP neural network receiver versus E_b/N_0 in a 10-user 'Near-Far' DS-CDMA channel.

Figure 6. 33 shows the BER performance of two receivers as a function of $E_i/E_{b(desired)}$ in a 'Near-Far' multiple-access DS-CDMA channel. In this case, the E_b/N_0 of the desired user's signal has been set at 6 dB whereas all co-channel interfering users' signals have an equal energy, E_i, in the channel. As it can be seen, the adaptive MMSE and the adaptive MLP neural network receivers have acceptable 'Near-Far' resistance in a wide range varying of interfering signals' energy. The BER performance of the adaptive MLP receiver in stronger MAI is better than the BER performance of the adaptive MMSE receiver and this is because of using non-linear elements in the structure of this receiver. The non-linear elements in the structure of the adaptive MLP neural network enable the receiver to distinguish between the wanted and unwanted signals. On the other hand, by increasing the energy of interfering signals in the DS-

CDMA channel, the probability of losing the phase lock on the weak desired user's signal in adaptive MMSE receiver, increases.
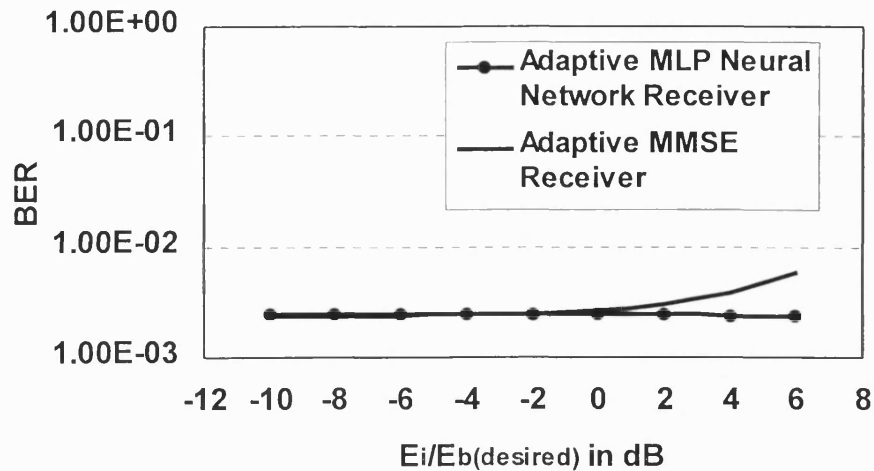
Figure 6. 33: The BER performance of the adaptive MMSE receiver and the adaptive MLP neural network receiver versus $E_i/E_{b(desired)}$ in a 10-user 'Near-Far' DS-CDMA channel.

Figure 6. 34 shows the BER performance of the adaptive MMSE and the adaptive MLP neural network receivers as a function of number of co-channel user in a 'Near-Far' multiple-access DS-CDMA channel. In this case, the E_b/N_0 of the desired user's signal has been set at 6 dB whereas the energy per bit of each co-channel interfering user signal is 6 dB higher than the energy per bit of the desired user's signal. In this case, a 'Near-Far' DS-CDMA environment has been assumed. As it can be seen, the adaptive MMSE and the adaptive MLP neural network receivers have acceptable performance in this 'Near-Far' DS-CDMA environment and the BER performance of two receivers are found to be approximately identical. The BER performance of the adaptive MLP neural network receiver is slightly better than the BER performance of the adaptive MMSE receiver. This is because, by increasing the number of strong co-channel interfering signals in the DS-CDMA channel, the probability of losing the phase lock on the weak desired user's signal in the adaptive MMSE receiver, increases.
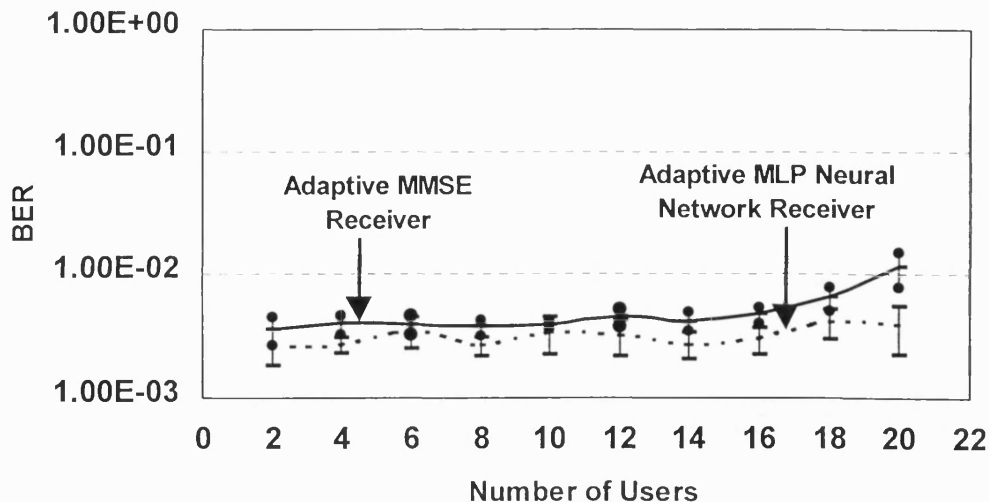
Figure 6. 34: The BER performance of the adaptive MMSE receiver and the adaptive MLP neural network receiver versus the number of co-channel user in a 'Near-Far' multiple-access DS-CDMA environment (both sets of error bars show 95% confidence limits assuming normal distribution).

The BER performance of the adaptive MMSE and the adaptive MLP neural network receivers as a function of E_b/N_0 in a 10-user multiple-access DS-CDMA and a 6-ray static multipath channel is shown in Figure 6. 35. The signature waveforms of all users have been chosen from a Gold code set with length 31 chips/bit. The energies of all co-channel user signals are identical and in this case a power-controlled environment has been assumed.

The adaptive MLP neural network receiver has been implemented by using a three-layer structure and a back-propagation algorithm has been used during the training mode to set the interconnection weights. In this case, different versions of the received signal via different rays in the multipath channel have been introduced as the wanted signals to the receiver. It is assumed that the adaptive MLP neural network receiver has information about the signature waveform of all co-channel users and the delay profile of the multipath channel during training mode. The adaptive MMSE receiver has been implemented by using a transversal structure with 31 tap weights and a NLMS adaptive algorithm has been employed to set the weight vector. Also preamble sequence for training the receiver has been used before transmitting the real data. In this case, the receiver could set its weight vector to detect the desired user's signal in the multiple-access and multipath channel.
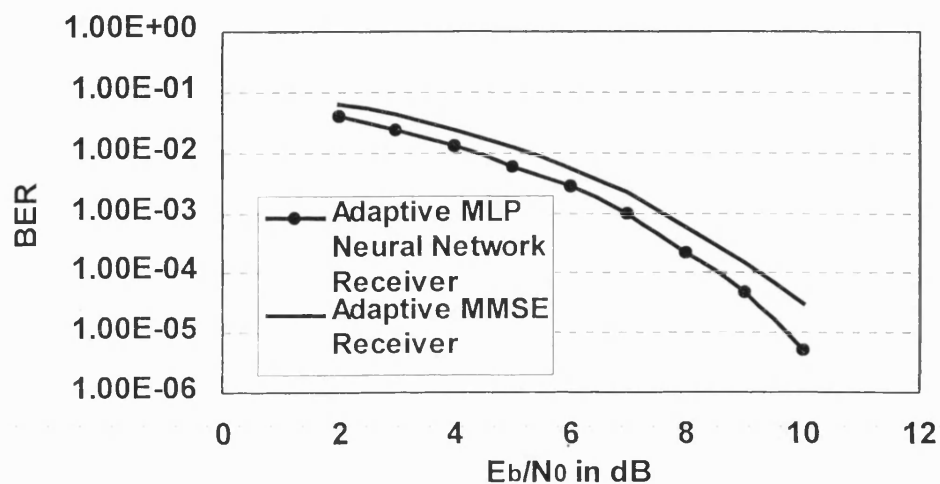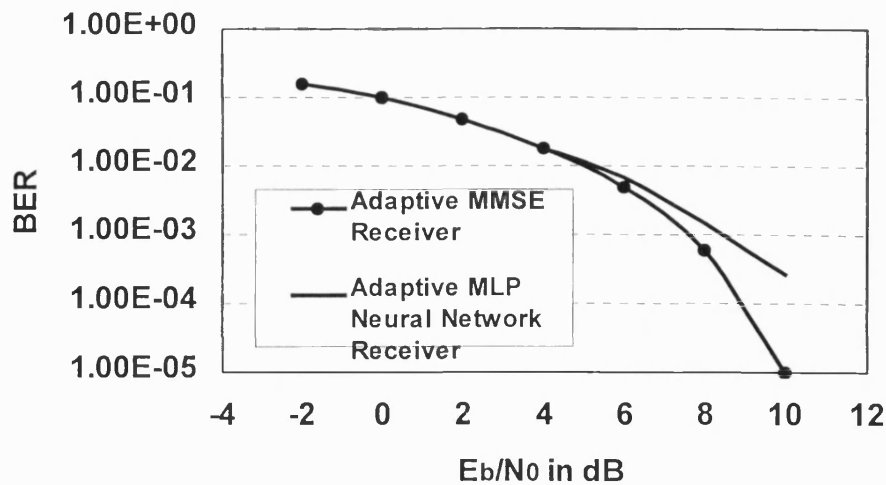
Figure 6. 35: The BER performance of the adaptive MMSE receiver and the adaptive MLP neural network receiver versus E_b/N_0 in a 10-user multiple-access DS-CDMA and 6-ray COST207 static multipath channel.

As can be seen, the BER performance of the adaptive MMSE and the adaptive MLP neural network receivers in the multiple-access DS-CDMA and the static multipath environment are approximately identical. They successfully detect the transmitted data and reject the MAI and combat the effect of multipath in the DS-CDMA channel. It is shown that the BER performance of the adaptive MMSE receiver in the higher E_b/N_0 is slightly better than the BER performance of the adaptive MLP neural network receiver. This is because, in the higher E_b/N_0, the probability of losing the phase lock on the desired user's signal decreases. In this situation, the ability of the adaptive MMSE receiver to collect different rays of propagated energy of the desired user's signal in the multipath channel, increases and the performance of the receiver is improved.

It should be noted that the adaptive MMSE receiver is able to function in a multiple-access DS-CDMA and multipath environment without any additional information about the signature waveforms of other co-channel users and the delay profile of the multipath channel whereas the adaptive MLP neural network receiver requires this information to distinguish between the wanted pattern and unwanted patterns. On the other hand, in an asynchronous mode of signal transmission, the adaptive MLP neural network requires to be trained with all delayed versions of the different signature waveforms of all users in the channel as the wanted and unwanted patterns. It is clear in this case, the training process will be very long and because of increasing

the number unwanted signals in the channel, the performance of receiver is degraded. The performance of the adaptive MMSE receiver in an asynchronous multiple-access DS-CDMA channel is as well as the synchronous mode of signal transmission.

6.4 Performance Evaluation of DS-CDMA Receivers in the Uplink Channel

For the uplink DS-CDMA channel, the receiver is a base-station, which is located in the centre of a communication cell and receives signal from different handsets in the cell. In this situation, the main task of the receiver is detecting the signal of all co-channel users, which are transmitting their signals simultaneously in the same band of frequency. In this case, a multi-user strategy should be employed to perform the receiver. The multi-user receiver, by utilising additional information such as the signature waveform of all active users in the cell, will be able to detect the transmitted data of co-channel users.

In this section, the performance of several multi-user receivers such as the maximum-likelihood receiver, the decorrelating receiver, the adaptive MLP neural network receiver and the recurrent neural network receiver will be evaluated in the different channel model scenarios in the multiple-access DS-CDMA channel.

6.4.1 Performance Evaluation of the Optimum Maximum-likelihood Receiver

To evaluate the performance of the maximum-likelihood receiver, which has the best performance as a multi-user receiver in the multiple-access DS-CDMA environment, a multi-user DS-CDMA channel with 'Near-Far' effect is simulated. This channel includes five co-channel interfering users, where all users are transmitting their data in a synchronous mode. The signature waveforms of all users have been chosen arbitrary with the length of 31 chips/bit. To simulate a 'Near-Far' environment in the DS-CDMA channel, the energy per bit of each co-channel user's signal is 5 dB higher than the energy per bit of the desired user's signal. The maximum-likelihood receiver has been performed by using a bank of matched filters followed by a processor, which calculates the correlation metrics for all possible choices of the bits in the information sequence of all co-channel users and select the sequence that gives the largest correlation metrics.

To observe the huge difference between the performance of the maximum-likelihood receiver and the conventional matched filter receiver in the DS-CDMA multiple-access environment, it is useful to compare the performance of two receivers. As it is known, these receivers have the marginal BER performance in this environment, where the maximum-likelihood receiver has the best performance and the conventional matched filter receiver has the poorest performance in the multiple-access DS-CDMA environment. In this way, the conventional matched filter receiver has been implemented in the same environment and under identical conditions.

Figure 6. 36 shows the BER performance of the maximum-likelihood receiver and the conventional matched filter receiver as a function of E_b/N_0 in a 5-user multiple-access DS-CDMA channel. The energy per bit of each interfering user is 5 dB more than the energy per bit of the desired user, which simulates the 'Near-Far' effect in the transmission channel.
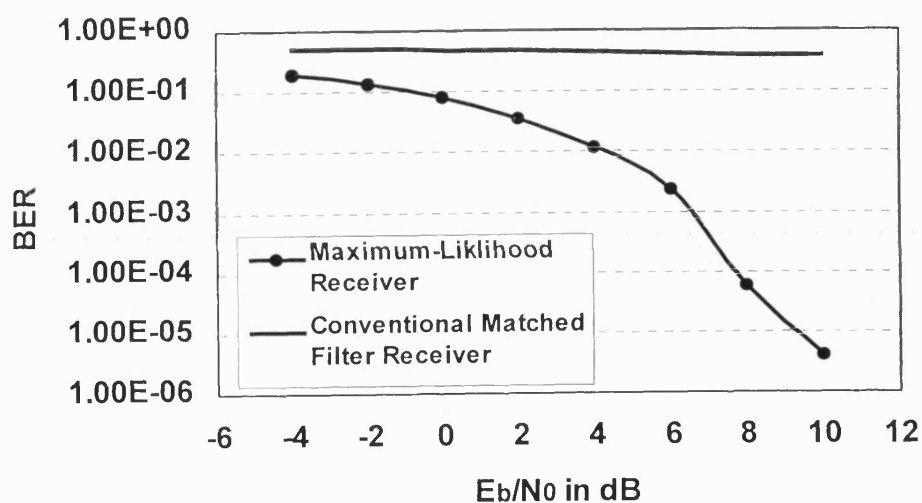
Figure 6. 36: The BER performance of the maximum-likelihood receiver and the conventional matched filter receiver versus E_b/N_0 in a 5-user 'Near-Far' multiple-access DS-CDMA environment.

Figure 6. 37 shows the BER performance of two receivers as a function of $E_i/E_{b(desired)}$ in a 5-users multiple-access DS-CDMA channel. The energy per bit of the desired user's signal has been set to obtain $E_{b(desired)}/N_0 = 5$ dB.

As can be seen, there is a significant difference between the BER performance of the maximum-likelihood receiver and the conventional matched filter receiver in the identical

power of co-channel interfering users and by increasing the power of interfering users, a huge degradation occurs in the BER performance of this receiver. On the other hand, the performance of the maximum-likelihood receiver is not sensitive to the 'Near-Far' problem and the BER performance of this receiver remains approximately constant by changing the energy per bit of the MAI in the multiple-access DS-CDMA channel.
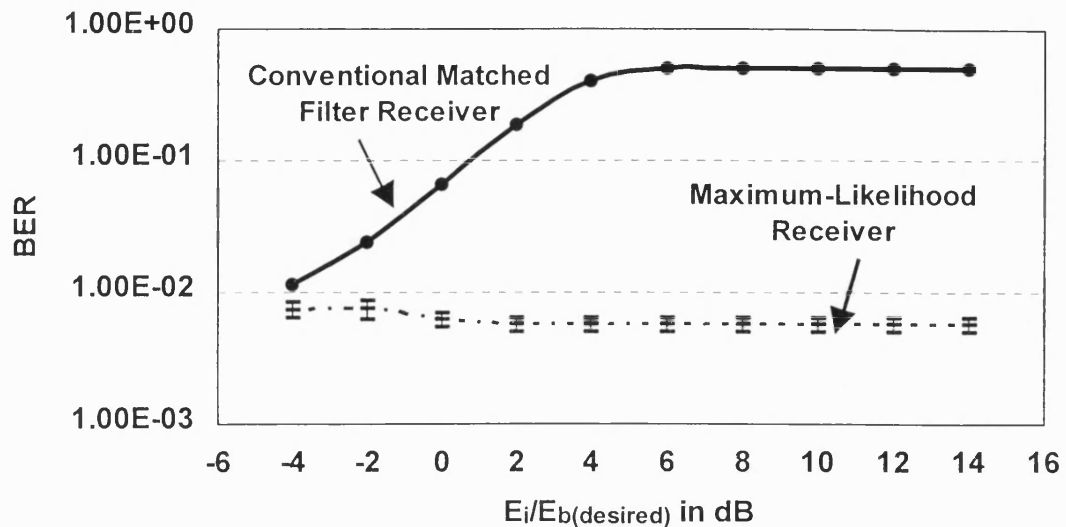
Figure 6. 37: The BER performance of the maximum-likelihood receiver and the conventional matched filter receiver as a function of $E_i/E_{b(desired)}$ in a 5-user multiple DS-CDMA environment (the error bars show 95% confidence limits assuming normal distribution).

As has been noted in chapter two, in the maximum-likelihood receiver, the notable performance gains over other types of receivers are obtained because of accessing all additional information including the signature waveform of all co-channel users, the received signal's amplitudes, and the timing of all co-channel users.

6.4.2 Performance Evaluation of the Decorrelating Receiver

To evaluate the performance of the decorrelating receiver in the multiple-access DS-CDMA environment, a multi-user channel with 'Near-Far' effect is simulated. This channel contains six interfering users, where the energy per bit of each co-channel user is 6 dB higher than the energy per bit of the desired user. To compare the performance of this receiver, the

conventional matched filter receiver and the maximum-likelihood receiver are also simulated in the same environment and under identical conditions. As it is known, these receivers have the marginal BER performance in this environment, where the maximum-likelihood receiver has the best performance and the conventional matched filter receiver has the poorest performance in the multiple-access DS-CDMA environment.

Figure 6. 38 and Figure 6. 39 show the BER performance of three receivers in two different channel model scenarios. Figure 6. 38 shows the BER performance of the decorrelating receiver, the maximum-likelihood receiver and the conventional matched filter receiver as a function of E_b/N_0 in a 6-user multiple-access DS-CDMA channel. In this case, the energy per bit of the received signal is the same for all users in the channel, which shows a power-controlled environment. As it could be predicted, the BER performance of the decorrelating receiver is better than the BER performance of the conventional matched filter receiver and poorer than the BER performance of the maximum-likelihood receiver, which is the optimum receiver in this case.
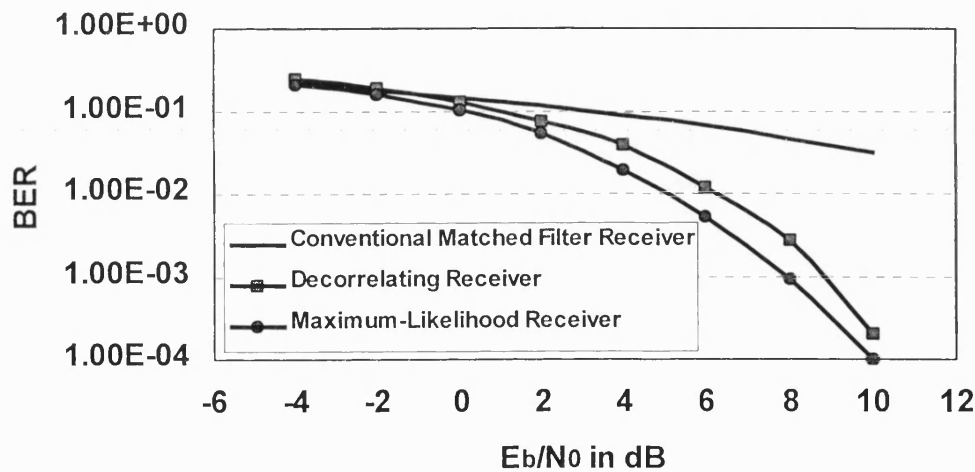
Figure 6. 38: The BER performance of the decorrelating receiver, the maximum-likelihood receiver, and the conventional matched filter receiver versus E_b/N_0 in a 6-user multiple-access DS-CDMA channel.

Figure 6. 39 shows the capabilities of three receivers in handling with imperfect power control of the various users due to the 'Near-Far' effect in the CDMA environment. In this case, the $E_{b(desired)}/N_0$ of the desired user's signal is set at 6 dB whereas all the co-channel other users have an equal energy per bit, E_i. As it can be seen, the BER performance of the decorrelating

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receiver is located between the BER performances of two other receivers. Figure 6. 39 also shows an important feature of the decorrelating receiver. It shows that the BER performance of the decorrelating receiver, such as the maximum-likelihood receiver, is independent of the energy per bit of the co-channel interfering users and it means that the decorrelating receiver is a 'Near-Far' resistance receiver.
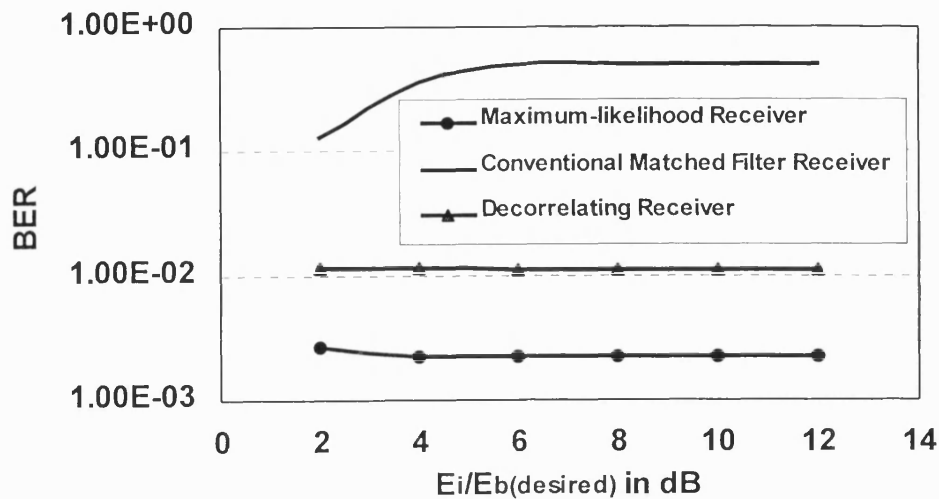
Figure 6. 39: The BER performance of the decorrelating receiver, the maximum-likelihood receiver, and the conventional matched filter receiver versus $E_i/E_{b(desired)}$ in a 6-user 'Near-Far' multiple-access DS-CDMA environment.

As can be seen the BER performance of this receiver, such as the maximum-likelihood receiver, does not change by increasing the energy per bit of the co-channel interfering user signals. It is because, the decorrelating receiver completely eliminates the effect of co-channel interfering signals or MAI on the desired user signal in the multi-user DS-CDMA environments.

The achieved results in this section show that the decorrelating receiver is a multi-user receiver with a good 'Near-Far' resistance in the DS-CDMA environment. The BER performance of this receiver is between the BER performance of the maximum-likelihood receiver and the BER performance of the conventional matched filter receiver. In the absence of information about the amplitudes of the received signals, the decorrelating receiver is the solution of applying the maximum-likelihood criterion in the DS-CDMA channel.

6.4.3 Performance Evaluation of the Multi-User Adaptive MLP Neural Network Receiver

In order to use the adaptive MLP neural network receiver as a multi-user receiver in the multiple-access DS-CDMA environment, it is needed to change the front-end structure of this receiver. In this way, a bank of matched filters should be used in the front end of the MLP neural network structure. The output signals of the matched filters in the bank are inserted into the input layer of MLP neural network. The number of nodes, in the input and the output layers, are equal to the number of co-channel users in the multiple-access DS-CDMA channel.

To verify the performance of the adaptive multi-user MLP neural network in a multiple-access DS-CDMA environment, a MLP neural network structure with 2 nodes in the input layer, 2 nodes in the hidden layer and 2 nodes in the output layer has been implemented in a 2-user channel. The known sequences have been employed to train the MLP neural network in the beginning of data transmission and interconnection weights and threshold values are set by using the back-propagation algorithm during learning mode. The spreading waveform sequences for two users have been chosen arbitrary with length 31 chips/bit and it has been assumed that the receiver knows these signature waveforms to despread the received signals in the bank of matched filter. The energy per bit of interfering user's signal is 6 dB more than the energy per bit of the desired user's signal that represents unequal power control or 'Near-Far' effect. To compare the BER performance, a conventional matched filter receiver has also been simulated in the same environment and under identical conditions.

The BER performance of the conventional matched filter receiver and the adaptive multi-user MLP neural network receiver as a function of E_b/N_0 in a 2-user 'Near-Far' multiple-access DS-CDMA channel is shown in Figure 6. 40. It can be seen that the adaptive multi-user MLP neural network receiver outperforms the conventional matched filter receiver in the presence of strong multiple-access interfering signal. In this situation, it has an acceptable performance for combating the effect of strong MAI in the DS-CDMA channel.
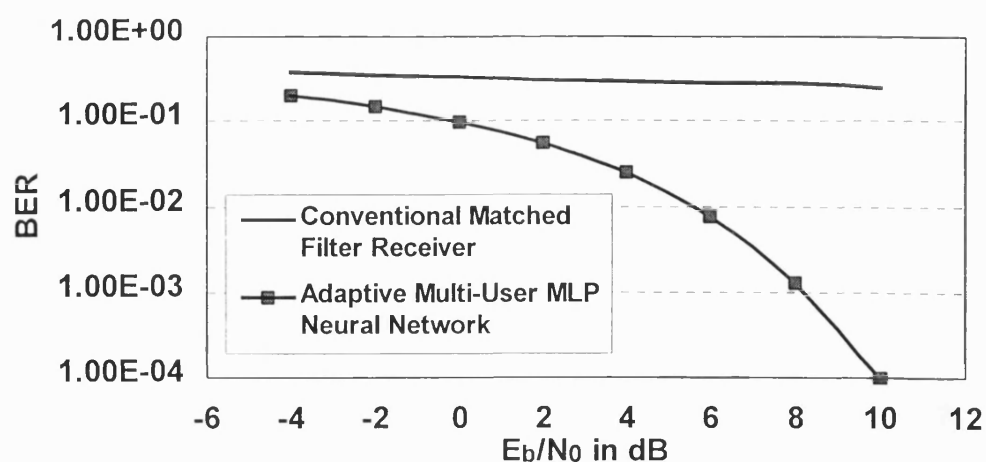
Figure 6. 40: The BER performance of the adaptive multi-user MLP neural network receiver and the conventional matched filter receiver versus E_b/N_0 in a 2-user 'Near-Far' multiple-access DS-CDMA channel.

6.4.4 Performance Evaluation of the Recurrent Neural Network Receiver

To verify the performance of the recurrent neural network receiver for detecting the DS-CDMA signal and combating the effect of co-channel other user interference in the multi-user environment; the optimum maximum-likelihood receiver, the recurrent neural network receiver, the conventional match filter receiver and the decorrelating receiver have been simulated. The spreading waveform sequences for all users have been chosen arbitrarily with length of 31 chips and the BPSK modulation is employed for all users in the DS-CDMA environment.

The recurrent neural network receiver uses the output signals of the bank of matched filters as the external input signals to the neural network. The cross-correlation of the user's signature waveform and the amplitude of the received signals are used as interconnection weight in the structure of this receiver. The receiver's parameters have been set as $I_j=2Y_j$, $x_j=A_jb_j$, $N=K$, and $w_{ji} = -2h_{ji}$, where I_j is the external input signal to the jth neurons, x_j is the output signal of activation function in neuron j, N is the number of neurones in the network and w_{ji} is the connection weight between the jth and the ith neurons. The self-connection factor, w_{kk}, is selected to be zero. It has been shown that under this assumption, the state of the system will always converge to a state, which has the global minimum energy [6- 5].

The BER performance of the conventional matched filter receiver, the decorrelating receiver and the neural network receiver as a function of E_b/N_0 are shown in Figure 6. 41. These results have been achieved in a 6-user DS-CDMA multiple-access channel. In this case, the energy per bit of all received signals at the receiver is assumed to be identical for all co-channel users. This case may be interpreted as a power-controlled environment. It can be seen that the recurrent neural network receiver outperforms the conventional matched filter and the decorrelating receivers in rejecting the co-channel MAI signals.
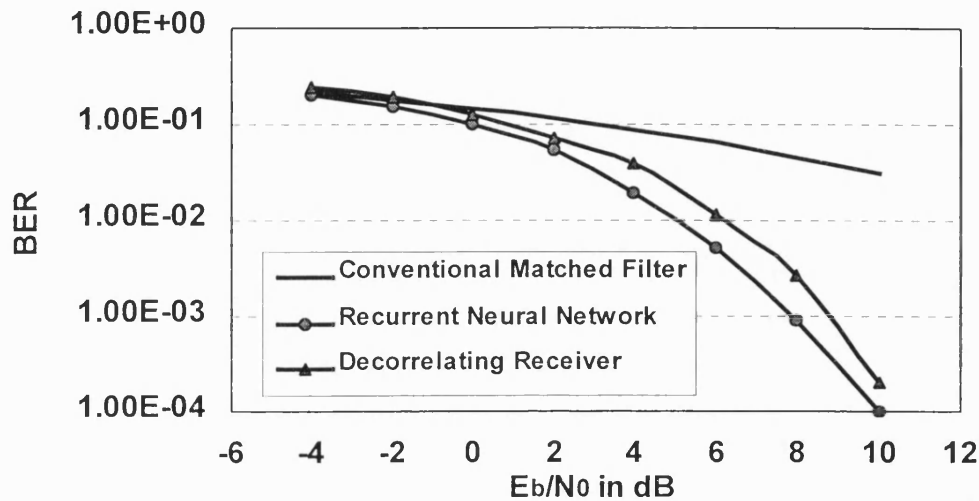
Figure 6. 41: The BER performance of the recurrent neural network receiver, the decorrelating receiver and the conventional matched filter receiver versus E_b/N_0 in a 6-user DS-CDMA multiple-access channel.

Figure 6. 42 shows the abilities of these receivers in handling with imperfect power control of the various co-channel users due to the 'Near-Far' effect in the CDMA environment. In this case, the E_b /N_0 of the desired user's signal has been set at 6 dB whereas all of the co-channel other users have an equal value of the energy per bit, E_i. As it can be seen, the BER performance of the recurrent neural network receiver is substantially better than both the conventional matched filter receiver and the decorrelating receiver.

As has been shown in chapter three, the optimum maximum-likelihood receiver computes the correlation metrics C(Y_K , b_K) for different combination of users' transmitted bits and chooses $\{b_k(n), 1 \leq k \leq K \}$ that maximise correlation metrics. It is clear that in this situation, the complexity grows exponentially by increasing the number of co-channel users. The number of addition and multiplication operation after bank of matched filters that should be done to

implement the optimum maximum-likelihood receiver are $2^K(K+2^K)$ additions and 2^K $[4(K/2+2^K)]$ multiplications respectively, where K is the number of co-channel user.
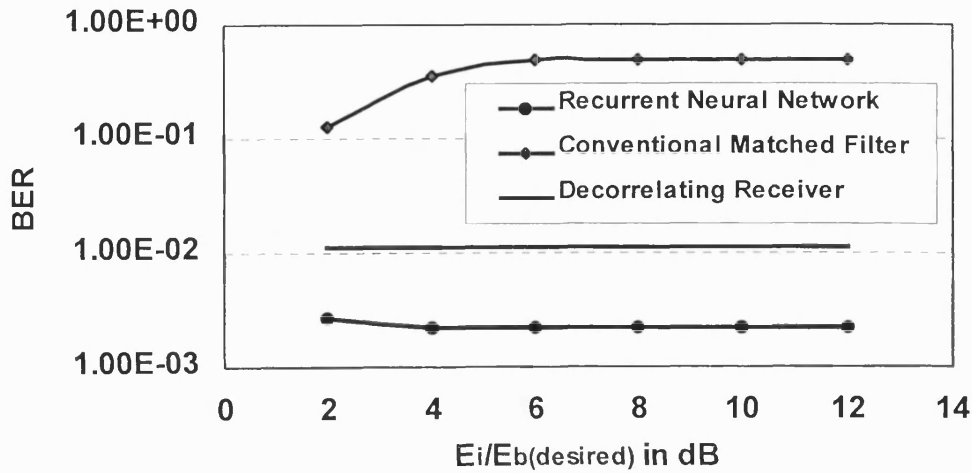
Figure 6. 42: The BER performance of the recurrent neural network receiver, the conventional matched filter receiver and the decorrelating receiver versus $E_i/E_{b(desired)}$ in a 6-user 'Near-Far' multiple-access DS-CDMA channel.

In the recurrent neural network receiver, the number of addition and multiplication operation after bank of matched filters, which is required to implement the receiver, are lower than K^2 adds and K^3 multiplies where K is the number of co-channel user. As it can be seen, in this system by increasing the number of co-channel user, the implementation complexity grows far slower than the optimum maximum-likelihood receiver.

To compare the performance of the maximum-likelihood receiver and the recurrent neural network receiver in a 'Near-Far' multiple-access DS-CDMA environment, the BER performance of these receivers have been obtained in different channel model scenarios. Table 6. 3 shows the BER performance of these receivers as a function of $E_{b(desired)}/N_0$ in the multiple-access DS-CDMA environment, where six co-channel users share the channel. In this case, the 'Near-Far' environment is simulated by allowing each of the co-channel user to transmit signal at a energy per bit that is 6 dB higher than the energy per bit of the desired user's signal, i.e. $E_i/E_{b(desired)}=6$ dB. It can be seen that in this situation, the BER performance of the recurrent neural network receiver is the same as the BER performance of the optimum maximum-likelihood receiver.

E_b/N_0 in dB	Optimum Maximum-Likelihood Receiver	Recurrent Neural Network Receiver
-4	0.18640	0.18696
-2	0.13002	0.13028
0	0.07715	0.07723
2	0.03664	0.03669
4	0.01178	0.01179
6	0.00231	0.00231
8	0.00006	0.00006

Table 6. 3: The BER performance of the maximum-likelihood receiver and the recurrent neural network receiver versus E_b/N_0 in a 6-user 'Near-Far' multiple-access DS-CDMA channel.

Table 6. 4 shows the BER performance of these receivers as a function of $E_i/E_{b(desired)}$ in a 6-user DS-CDMA environment, where $E_{b(desired)}/N_0 = 6$ dB for the desired user's signal. The result shows that the BER performance of the recurrent neural network receiver is found to be identical to the BER performance of the optimum maximum-likelihood receiver in the 'Near-Far' multiple-access DS-CDMA environment.

$E_i/E_{b(desired)}$ in dB	Optimum Maximum-Likelihood Receiver	Recurrent Neural Network Receiver
2	0.00231	0.00227
4	0.00231	0.00233
6	0.00231	0.00231
8	0.00231	0.00231
10	0.00231	0.00231
12	0.00231	0.00231
14	0.00231	0.00231

Table 6. 4: The BER performance of the optimum maximum-likelihood receiver and the recurrent neural network receiver versus $E_i/E_{b(desired)}$ in a 6-user 'Near-Far' multiple-access DS-CDMA environment.

Table 6. 5 shows the BER performance of these receivers in a 'Near-Far' multiple-access DS-CDMA environment as a function of the number of co-channel user. In this situation, the BER performance of the recurrent neural network receiver is the same as the BER performance of the optimum maximum-likelihood receiver.

Number of Co-Channel Users	Optimum Maximum-Likelihood Receiver	Recurrent Neural Network Receiver
2	0.00231	0.00231
4	0.00231	0.00231
6	0.00231	0.00231
8	0.00231	0.00231
10	0.00231	0.00231

Table 6. 5: The BER performance of the optimum maximum-likelihood receiver and the recurrent neural network receiver versus the number of co-channel users in a 'Near-Far' multiple-access DS-CDMA channel.

In the receivers, which are implemented by using fixed optimised parameters in their structure such as the optimum maximum-likelihood receiver and the recurrent neural network receiver, the performance may be affected by changing the optimised value of parameters. To compare the sensitivity of the recurrent neural network receiver to this effect, a noisy term has been added to the each element of the correlation matrix. In this way, the added noise was a Gaussian noise with a mean value of zero and a variance value of one and a coefficient controlled the energy of the added noise. Table 6. 6 shows the BER performance of the recurrent neural network and the optimum maximum-likelihood receivers in a 2-user multiple-access DS-CDMA environment with $E_{b(desired)}/N_0=6$ dB for the desired user and $E_i/E_{b(desired)}=6$ dB that shows the 'Near-Far' effect in the channel. It can be seen that by increasing the power of added noise to the elements of the correlation matrix, the BER performance of two receivers degrade but the degradation are found to be identical in the two cases.

Added Noise Coefficient	Optimum Maximum-Likelihood Receiver	Recurrent Neural Network Receiver
0	0.0022	0.0022
0.001	0.0022	0.0022
0.005	0.0022	0.0022
0.01	0.0023	0.0023
0.05	0.0022	0.0022
0.1	0.0022	0.0022
0.5	0.0114	0.0114
1	0.0734	0.0734

Table 6. 6: The BER performance of the optimum maximum-likelihood receiver and the recurrent neural network receiver in a 2-user 'Near-Far' multiple-access DS-CDMA environment with mismatched parameters.

The implementation complexity[7] of two receivers versus different number of co-channel user is shown in Table 6. 7. As it can be seen, by increasing the number of co-channel user in the DS-CDMA channel, the difference between the implementation complexity of the optimum maximum-likelihood receiver and the recurrent neural network receiver increases. For example, in a 6-user multiple-access channel model scenario, the optimum maximum-likelihood receiver needs 4480 addition and 17152 multiplication to be implemented, where the recurrent neural network receiver requires lower than 36 addition and 216 multiplication.

The investigation of the performance of the recurrent neural network receiver as a multi-user receiver in the multiple-access DS-CDMA environment shows that this receiver is extremely suitable for combating the effect of co-channel interference and its performance is found to be identical to the maximum-likelihood receiver. In addition the implementation complexity of the recurrent neural network receiver, especially in the large number of co-channel users, is considerably lower than the implementation complexity of the maximum-likelihood receiver. Also the performance of the recurrent neural network receiver in an environment with changing optimised parameters is found to be identical to the maximum-likelihood receiver.

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[7] The implementation complexity of the recurrent neural network receiver in Table 6. 7 shows the higher level of complexity, which is needed for implementing this receiver.

Number of Co-Channel Users	Optimum Maximum-Likelihood Receiver	Recurrent Neural Network Receiver
2	24X+80Y	4X+8Y
4	320X+ 1152Y	16X+64Y
6	4480X+ 17152Y	36X+ 216Y
8	67584X+ 266240Y	64X+ 512Y

Table 6. 7: Comparison of the implementing complexity of the optimum maximum-likelihood receiver and the recurrent neural network receiver versus the number of co-channel user in multi-user DS-CDMA environment (X= number of additions, Y= number of multiplications).

The good performance and low implementation complexity of the recurrent neural network receiver make it attractive for the next generation of wireless mobile system.

6.5 Summary

In this chapter, the performances of several different DS-CDMA receivers in the spread spectrum communication system have been evaluated by using the Monte-Carlo simulation technique. The simulations are based on a 31 chip spreading sequences which is much shorter than that used in practical systems. It is possible that the performance advantages of the receiver architectures illustrated in this thesis are therefore optimistic. For the downlink channel, where the strategy is to use a single-user receiver to detect the desired user's signal, the conventional matched filter receiver, the RAKE receiver, the adaptive MMSE receiver and the adaptive MLP neural network receiver have been considered.

It is shown that the conventional matched filter receiver that is the simplest DS-CDMA receiver and has the best performance in the single-user Gaussian channel, is unable to function in a 'Near-Far' multiple-access environment. It has been shown that the performance of this receiver is very sensitive to the amount of MAI, which is produced by the cross-correlation value of signature waveform pairs and is increased by the 'Near-Far' effect in the channel. In this case,

by increasing the power of MAI, the BER performance of this receiver degrades. It is clear that the conventional matched filter receiver is not suitable to be used as a practical single-user receiver in the multiple-access DS-CDMA environment. It has been shown that the RAKE receiver, which is the best receiver for collecting different rays of propagated energy of the transmitted signal in a single-user multipath DS-CDMA channel, loses its ability to function in the multiple-access environment. It has been shown that the performance of this receiver, degrades because of MAI in the multiple-access environment and it is not able to combat the effect of MAI in the channel.

It has been considered that the adaptive MMSE receiver, as a single-user receiver in the DS-CDMA system, can be employed to detect the desired user's signal in a multiple-access environment. The result showed that it has the capability to perform a conventional matched filter receiver in a single-user Gaussian channel, where the conventional matched filter receiver has the best performance. In the multipath single-user DS-CDMA channel, where the RAKE receiver has the best performance, the performance of the adaptive MMSE receiver is found to be identical to the RAKE receiver. The 'Near-Far' resistance of the adaptive MMSE receiver in the multiple-access DS-CDMA environment is the most important advantage of this receiver. The achieved results have shown that the adaptive MMSE receiver is able to detect the desired user's signal between strong co-channel interference signals. In the multi-user DS-CDMA environment, where the desired user's signal is propagated via different rays in the multipath channel, the adaptive MMSE receiver despreads the desired user's data, combats the effect of multipath and rejects the co-channel other user signals. In order to function in the multipath-fading channel, the adaptive MMSE receiver has been modified. It has been shown that the BER performance of the modified adaptive MMSE receiver in the multipath-fading channel mostly depends on the quality of estimating the channel characteristics. The Maximal Ratio Combining (MRC) technique, which is known as a good estimation technique in the DS-CDMA environment, has been employed to estimate the delay profile and attenuation coefficients of the multipath-fading channel. The result is shown that the modified adaptive MMSE is a suitable receiver for rejecting the MAI in the multipath-fading mobile channels.

The adaptive MLP neural network receiver has the potential to be used as a single-user DS-CDMA receiver in the multiple-access environment. In this way, subtle boundaries can be performed, via a learning process, to separate the desired user's signature waveform as the wanted signal and co-channel interfering user's signature waveforms as the unwanted signals. It has been shown that the adaptive MLP neural network receiver, as a single-use receiver, has excellent 'Near-Far' resistance in the multiple-access DS-CDMA channel. The performance of the adaptive MLP neural network receiver has been investigated in the multipath DS-CDMA

channels. It has been shown that in the static multipath channel, the adaptive MLP neural network receiver, through the training process, learns to collect different rays of the propagated signal of the desired user in the channel. However the ability of this receiver for rejecting the co-channel interfering users' signals in the Rayleigh multipath-fading decreases by increasing the mobility of the receiver that interprets as the increasing of the Doppler frequency in the channel. But it has an acceptable performance in the low rate time varying multipath-fading and the multiple-access channels.

For the uplink channel, the strategy is to use a multi-user receiver to detect all co-channel user's signals. In this situation, the conventional matched filter receiver, the optimum maximum-likelihood receiver, the decorrelating receiver, the adaptive MLP neural network receiver and the recurrent neural network receiver have been considered. The achieved results showed that the conventional matched filter receiver is very sensitive to the power of co-channel interfering users and by increasing the power of interfering users, a huge degradation in the BER performance of this receiver occurred. On the other hand, the performance of the maximum-likelihood receiver is not sensitive to the 'Near-Far' problem and the BER performance of this receiver remains approximately constant when changing the energy per bit of co-channel interfering users' signals in the multiple-access DS-CDMA channel.

The performance investigation of the decorrelating receiver showed that this receiver is a multi-user receiver with a good 'Near-Far' resistance in the DS-CDMA environment. It has been shown that its BER performance is between the BER performance of the maximum-likelihood receiver and the conventional matched filter receiver. It has been shown that the adaptive multi-user MLP neural network receiver outperforms the conventional matched filter receiver to detect transmitted signals in the presence of strong MAI signals. In this situation, it has an acceptable performance for combating the effect of strong MAI in the DS-CDMA channel.

The investigation of the performance of the recurrent neural network receiver as a multi-user receiver in the multiple-access DS-CDMA environment has shown that this receiver is extremely suitable for combating the effect of co-channel interference and its abilities are found to be identical to the maximum-likelihood receiver. In addition, the implementation complexity of the recurrent neural network receiver, especially for a large number of users, is lower than the implementation complexity of the maximum-likelihood receiver. Also the performance of the recurrent neural network receiver in an environment with non-optimised parameters is found to be identical to the maximum-likelihood receiver. These features make this receiver attractive candidate for use in the next generation of wireless mobile systems.

6.6 References

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Chapter Seven

Conclusions and Future Work

7.1 Introduction

The Code-Division Multiple-Access technique is a candidate for use in the third generation of the mobile communication. The main advantage of this technique is that it has the potential to accommodate more co-channel users in a given bandwidth than the other multiple-access techniques. In this case, the 'Near-Far' effect, whereby the desired user's signal is subject to interference from other strong co-channel interfering users' signals, degrades the performance of DS-CDMA system. This phenomenon exists because it is not possible to use an orthogonal set of signature waveforms to spread the data of all co-channel users in a mobile environment and hence a degree of multiple-access interference between co-channel users exists. It is estimated, by using conventional receivers for an asynchronous DS-CDMA mobile system, the number of users that can be accommodated in the 'Near-Far' channel is just up to 5% of the signature waveform length [7- 1]. Hence MAI rejecting receivers with good 'Near-Far' resistance property should be employed to improve the performance of the DS-CDMA scheme.

The work presented in this thesis has focused attention on MAI rejecting receivers in the DS-CDMA environment. In this way the theory, design, and performance of the adaptive MMSE receiver for downlink DS-CDMA mobile radio systems have been studied. Also the abilities of artificial neural network structures for use as a single-user receiver for the downlink DS-CDMA channel and a multi-user receiver for the uplink DS-CDMA channel have been considered. The proposed structures have attractive features that provide an alternative to the conventional techniques for combating the effect of 'Near-Far' problems in DS-CDMA communications.

7.2 Conclusions

In this work, a DS-CDMA system simulation has been developed and employed to evaluate both the proposed adaptive structures as single-user receivers for the downlink wide-band mobile channel, and the recurrent neural network as a multi-user receiver for the uplink wide-band mobile channel. The Monte Carlo simulation technique has been employed to examine the performance of the receivers in the different channel model scenarios. The performances of these receivers have been compared with the conventional and optimum receivers for the downlink and the uplink channels.

In the simulation, the DS-CDMA channel included multiple-access interference, thermal noise, multipath effects (static and dynamic), and the 'Near-Far' effect. For the downlink mobile channel, where the strategy is to use a single-user handset receiver to detect the desired user's signal, the conventional matched filter receiver, the RAKE receiver, the adaptive MMSE receiver and the adaptive MLP neural network receiver have been examined. For the uplink channel, where the strategy is to use a multi-user receiver to detect all of the co-channel user's signals, the conventional matched filter receiver, the optimum maximum-likelihood receiver, the decorrelating receiver, the adaptive MLP neural network receiver and the recurrent neural network receiver have been examined.

7.2.1 Adaptive Receivers for the Downlink channel

For the downlink channel, the single-user receiver is a handset and is employed to receive the desired user's signal in the multiple-access DS-CDMA environment. The adaptive receivers proposed in this thesis attempt to remove the co-channel interference from the received signal. The training process and their inherent pattern recognition ability enable them to perform subtle boundaries between wanted and unwanted signals in the DS-CDMA environment. The 'Near-Far' resistance of these receivers allows them to function in the multiple-access environment, which contains strong co-channel interfering users.

♦ Adaptive MMSE Receiver

The performance of the adaptive MMSE receiver in the downlink mobile channel has been evaluated. It has been shown that the adaptive MMSE receiver, as a single-user receiver in the DS-CDMA system, can be employed to detect the desired user's signal in a multiple-access environment. The convergence performance of this receiver, measured by the mean square error at the output of receiver, was very good in the presence of significant levels of multiple-access interference. The achieved result shows that for the typical configuration, 900 MHz carrier frequency and 3 MHz chip rate, a satisfactory convergence level is achieved in less than 10 ms.

The performance of the adaptive MMSE receiver, which has been achieved in several different channel model scenarios, shows that this receiver has a good ability for use as a single-user receiver in the DS-CDMA mobile channel. The BER performance of this receiver in the single-user Gaussian channel was found to be identical to the conventional matched filter receiver, which has the best available performance. In the multipath single-user DS-CDMA channel, the performance of the adaptive MMSE receiver was the same as the RAKE receiver, which has the

best available performance. The good 'Near-Far' resistance of the adaptive MMSE receiver in the multiple-access DS-CDMA environment is the most important feature of this receiver. The achieved results show that the adaptive MMSE receiver is successful in detecting the desired user's signal among the strong co-channel interfering signals. In the multipath and multiple-access DS-CDMA system, where the desired user's signal is propagated via different rays toward the receiver in the channel, the adaptive MMSE receiver was able to despread the desired user's data, combat the effect of multipath and reject the co-channel interfering user signals simultaneously.

In order to improve the ability of the adaptive MMSE receiver to function in a dynamic multipath-fading DS-CDMA channel, the structure of this receiver has been modified. The novel modification includes some systems, which are employed to estimate the delay profile and attenuation coefficients of the dynamic multipath-fading channel and remove the fast varying channel's effect on the received signal. In this case, the Maximal Ratio Combining (MRC) technique has been employed to estimate the parameters of the dynamic multipath-fading channel. The achieved results show that the performance of the new modified adaptive MMSE receiver in the dynamic multipath-fading channel mostly depends on the quality of the estimation technique which is employed to obtain the parameters of the multipath channel. It is clear, by decreasing the level of noise and improving E_b/N_0 in the DS-CDMA channel, the error in the estimation is reduced and the performance of the receiver increases. The performance evaluation of the modified adaptive MMSE receiver in the dynamic multipath-fading channel with different Doppler frequencies shows that it has a good ability to reject MAI in this environment.

♦ Adaptive MLP Neural Network Receiver

The adaptive MLP neural network receiver has the potential for use as a single-user DS-CDMA receiver in the multiple-access environment. The non-linear processing units in the structure of the artificial neural network, via the learning process, allow the receiver to distinguish between the wanted and unwanted signals in the multiple-access DS-CDMA environment and hence achieve a good 'Near-Far' resistance over a wide range of interfering power levels. The performance of the adaptive MLP neural network receiver, which have been achieved in several different channel model scenarios, shows that this receiver has a good ability for use as a single-user receiver in the DS-CDMA mobile channel. The BER performance of this receiver in the single-user Gaussian channel was found to be identical to the conventional matched filter receiver, which has the best available performance. The achieved results show that the adaptive

MLP neural network receiver, as a single-use receiver, has excellent 'Near-Far' resistance in the multiple-access DS-CDMA channel.

The performance of the new adaptive MLP neural network receiver has been investigated in the multipath DS-CDMA channel. In this case, the delay profile of the multipath channel should be known in advance in the receiver. During the training mode, different versions of the desired user's signal, which have been propagated via different rays in the multipath channel, are introduced as the wanted signals. The achieved results show that in the static DS-CDMA multipath channel, the adaptive MLP neural network receiver learns to collect different rays of the propagated signal of the desired user and rejects the MAI in the multiple-access channel. However the ability of this receiver to reject the multiple-access interference in the Rayleigh multipath-fading environment decreases when increasing the Doppler frequency in the channel, but it has acceptable performance in the low rate time varying multipath-fading and multiple-access channels. It means that the adaptive MLP neural network receiver may be employed as a single-user receiver in a low speed mobile channel such as used in the military environment.

7.2.2 Multi-User Neural Network Receivers in Uplink Channel

In the uplink mobile channel, the multi-user receiver is located in the centre of the cell and receives all co-channel user signals in the multiple-access DS-CDMA environment. To improve the performance of signal detection, multi-user receivers proposed in this thesis attempt to use all available additional information in the multi-user environment. In this way, the signature waveform of the co-channel users, the amplitude of the received signals and the timing of all received signals are employed to perform the best distinction in the signal space between different user's patterns in the DS-CDMA environment. The adaptive MLP neural network and the recurrent neural network are two types of multi-user DS-CDMA receiver that have had their performance examined and compared with other multi-user receivers in this work.

◆ Adaptive Multi-User MLP Receiver

The adaptive MLP multi-user neural network receiver can be used as a multi-user DS-CDMA receiver in the multiple-access environment. The achieved result has shown that the adaptive multi-user MLP neural network receiver has good 'Near-Far' resistance in the multiple-access DS-CDMA channel. It has been shown that the adaptive multi-user MLP neural network receiver outperforms the conventional matched filter receiver in detecting the transmitted

signals in the presence of strong MAI signals. In this situation, it has an acceptable performance as a multi-user receiver.

◆ Recurrent Neural Network Receiver

The recurrent neural network receiver has a suitable topology for use as a multi-user DS-CDMA receiver in the multiple-access environment. The non-linear processing units, the linear feedback links and the weighting factors in the structure of this receiver enable it to have a dynamical behaviour that leads the network toward the stable state with the minimum level of energy.

The achieved results have shown that this receiver is extremely good at combating the effect of co-channel interference and the performance and abilities of this receiver are identical to the maximum-likelihood receiver. It has been shown that the recurrent neural network receiver outperforms the conventional matched filter receiver and the decorrelating receiver in detecting the transmitted signals in the presence of strong MAI signals. In addition, the implementation complexity of the recurrent neural network receiver, especially for a large number of users, is lower than the implementation complexity of the maximum-likelihood receiver. Finally, the performance of the recurrent neural network receiver in an environment with non-optimised parameters is identical to that of the maximum-likelihood receiver. These features make this receiver attractive for use in the next generation of wireless mobile systems.

7.3 Future Work

The work described in this thesis has highlighted a number of areas that can be investigated in the future and these are listed within this section.

7.3.1 Adaptive Algorithms

To improve the ability of the adaptive receivers to follow the varying phase of the desired user's signal in the fast time varying multipath DS-CDMA channels, it is required to use a fast convergence algorithm with good stability. In the adaptive MMSE receiver, the LMS algorithm has a good stability but its convergence time is long. On the other hand, the RLS adaptive algorithm is a faster adaptive algorithm than the LMS algorithm, but its complexity is high and because of different sampling rates in the input and output ports of the proposed MMSE

receiver, it can not be used in this application. For the adaptive MLP neural network, back-propagation is a well-known algorithm for static applications and it has been shown that it can be employed in the slow time varying mobile environment. To improve the performance of the adaptive MLP neural network in the fast time varying mobile environment, it requires a new adaptive algorithm to be introduced for dynamic applications. The explicit study of optimum adaptive algorithms for use in the fast time varying mobile channel is an open area for future work.

7.3.2 Multipath-Fading Channel Estimation Techniques

The adaptive receivers lose phase lock on the desired user's signal in the fast time varying multipath-fading channels. In this case, the effect of the multipath channel on the desired user's signal should be compensated. However in a wide-band DS-CDMA mobile channel, the estimation procedures are very sensitive to the amount of MAI and the level of noise in the channel. To improve the performance of the DS-CDMA receiver in the fast time varying mobile channel, new techniques for estimating the channel impulse response, that are less sensitive to the level of interference and noise in the channel, should be investigated.

Another method, which seems to be useful for compensating for the effect of the multipath-fading channel, is utilising the concept of Orthogonal Frequency Division Multiplexing (OFDM) in the transmission of signals [7- 2], [7- 3]. By using OFDM techniques, the wide-band DS-CDMA channel will be divided into some narrow band sub-channels, where the fading seems to be flat in each sub-channel. In this case, the channel estimator should estimate and remove the effect of flat-fading on the desired received signal in each sub-channel. This idea may be a new direction for future work, which employs the OFDM technique for combating the effect of fast time varying mobile channel.

7.3.3 Using Radial Basis Functions as DS-CDMA Receivers

The MLP neural network has the potential for use as single-user and multi-user DS-CDMA receivers in wireless mobile channels. Also the topology of the recurrent neural network receiver makes it attractive for use as a multi-user detector in base-station of the mobile cell. The radial basis function is another type on the family of artificial neural networks that can be employed as an adaptive receiver in DS-CDMA mobile channel [7- 4], [7- 5]. In this way, by

using a suitable set of non-linear functions and optimising them, the receiver is able to function adaptively when detecting the desired user's signal in the DS-CDMA mobile channel.

7.4 References

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Appendix A

Pseudorandom Codes for DS-CDMA Systems

A.1 Introduction

The spreading sequences or signature waveforms have an important rule and are very important in the DS-CDMA communication. The periodic auto-correlation function (PACF) and the periodic cross-correlation function (PCCF) of spreading sequences are the main factors, which determine the abilities of these signal for use as signature waveforms in the spread spectrum communication. These functions are defined as bellow:

$$\theta_{cc}(k) = \frac{1}{N}\sum_{n=0}^{N-1} c_n c_{n+k} \qquad k = 0,1,\ldots,N \tag{A-1}$$

$$\theta_{cg}(k) = \frac{1}{N}\sum_{n=0}^{N-1} c_n g_{n+k} \qquad k = 0,1,\ldots,N \tag{A-2}$$

In equation (A-1) and equation (A-2), $\theta_{cc}(k)$ and $\theta_{cg}(k)$ are PACF and PCCF respectively and $c(t)$ and $g(t)$ are two unit amplitude [± 1] spreading sequences with a period of $T = NT_c$. Since $c(t)$ and $g(t)$ are periodic signals with the period of T, $\theta_{cc}(k)$ and $\theta_{cg}(k)$ are periodic with the same period. The maximum magnitude of the out-of-phase PACF of the $c(t)$ can be defined as:

$$\theta_{cc(\max)} = \max_{0<k<N}\left|\theta_{cc}(k)\right| \tag{A-3}$$

And the maximum magnitude of the PCCF between two signature sequences $c(t)$ and $g(t)$ is given by:

$$\theta_{cg(\max)} = \max_{0 \le k \le N}\left|\theta_{cg}(k)\right| \tag{A-4}$$

In the ideal case, where the values of $\theta_{cc(\max)}$ and $\theta_{cg(\max)}$ are zero, the signature waveforms perform an orthogonal set. Minimising the value of $\theta_{cc(\max)}$ and $\theta_{cg(\max)}$ is the criterion for selecting the signature sequence set to design the DS-CDMA system. It is clear that the signature waveform set with the lower value of $\theta_{cg(\max)}$ and $\theta_{cc(\max)}$, is more suitable for use in the DS-CDMA system because it generates lower amount of multiple-access interference in the DS-CDMA communication environment.

In this Appendix, two most famous types of the pseudorandom sequences, which are suitable for use as the signature waveform sets in the DS-CDMA communication system, are investigated. In this way, the generation technique of these sequences is explained and the performance of them are evaluated via computer simulation.

A.2 Maximal Length (ML) Sequences

The maximal-length (ML) sequence is the first set, which is suitable for use in the DS-CDMA communication system. A linear feedback shift register can be utilised to generate the ML sequence. For a feedback shift register with a linear feedback, which includes n stages in its structure, the maximum length of the generated ML sequence, N, is as below:

$$N=2^n-1 \tag{A-5}$$

It means that a 3-stage feedback shift register can be employed for generating the ML sequence with the length of 7 chips. The structure of n-stage feedback shift register for generating a ML sequence is shown in Figure A. 1. It includes n shift registers, which are connected in serial. A summer is employed to add signals of determined registers and the result is feed back to the input terminal of the circuit. In the beginning, the circuit is loaded by a non-zero seed and after that different chips of the ML sequence will be appear in the output of the circuit by each clock pulse.

The location of feedback lines in the circuit for generating the ML sequence can be interpreted as a polynomial. To achieve a ML sequence, it is necessary to select the feedback polynomial from the set of irreducible polynomials[1].

All ML signature sequences contain $2^{(n-1)}$ ones and $2^{(n-1)}-1$ zeros. Figure A. 2 shows the frequency spectrum of a 255-chips ML sequence. The ML sequence has been achieved by using an 8-stage feedback shift register circuit. As it can be seen, the ML sequence has a frequency spectrum that is like as a sinc(.) function.

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[1] These polynomials which are characteristic polynomials of ML codes, are called *primitive* polynomials. A table of them is given in [A- 1] and [A- 3].
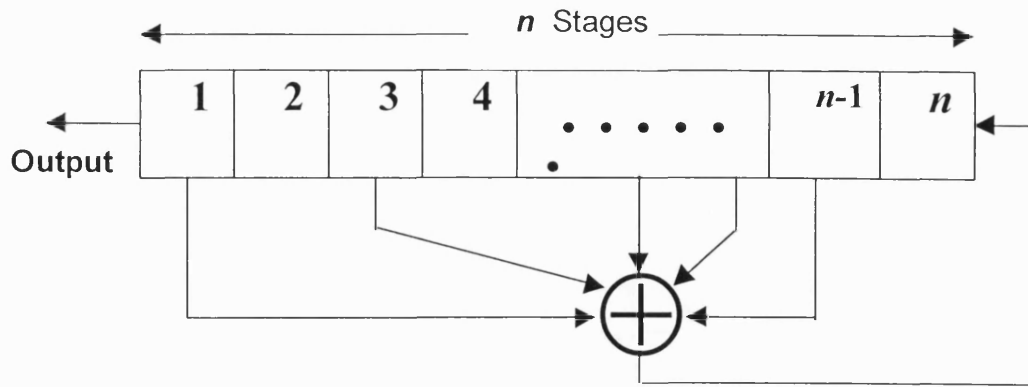
Figure A. 1: The structure of an *n*-stage shift register with linear feedback.
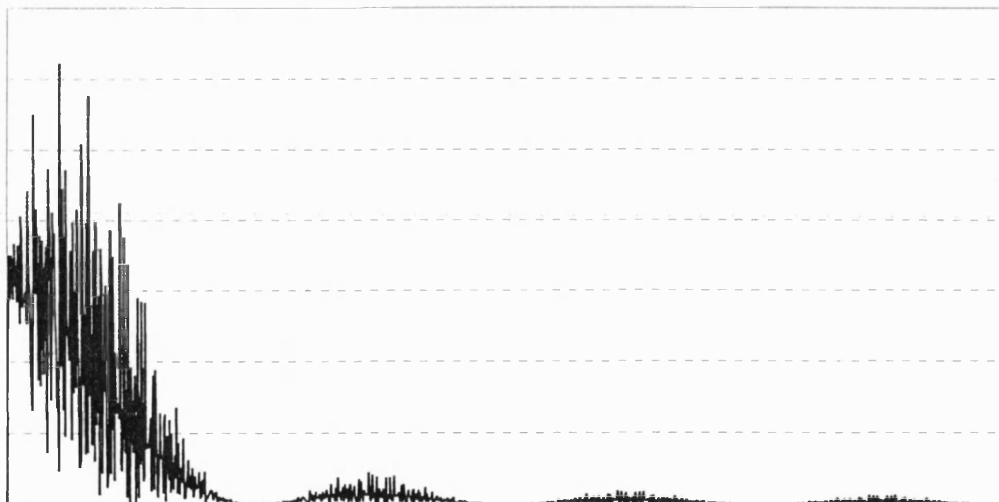
Figure A. 2: Frequency spectrum of a 255-chip ML sequence.

The PACF of a ML sequence is a two-valued function and is given by [A- 3]:

$$\theta_{cc}(k) = \begin{cases} 1.0 & k = lN \\ \\ -\dfrac{1}{N} & k \neq lN \end{cases}$$

(A-6)

In equation **(A-6)**, l is any integer and N is the sequence period. Figure A. 3 shows the PACF of a 255-chip ML sequence, which has been obtained via a computer simulation. As it can be seen, the ML sequence is characterised by a flat periodic auto-correlation side-lobes that provides a good approximation for the ideal short spreading sequence for use in the DS-CDMA systems.

Figure A. 3: Periodic Auto-Correlation Function (PACF) of a 255-chip ML sequence.

Figure A. 4 shows the PCCF of a 255-chip ML sequence, which has been obtained via a computer simulation. The cross-correlation function between any pair of ML sequences of the same period has relatively large peaks that are unacceptable for DS-CDMA applications [A- 4].

199
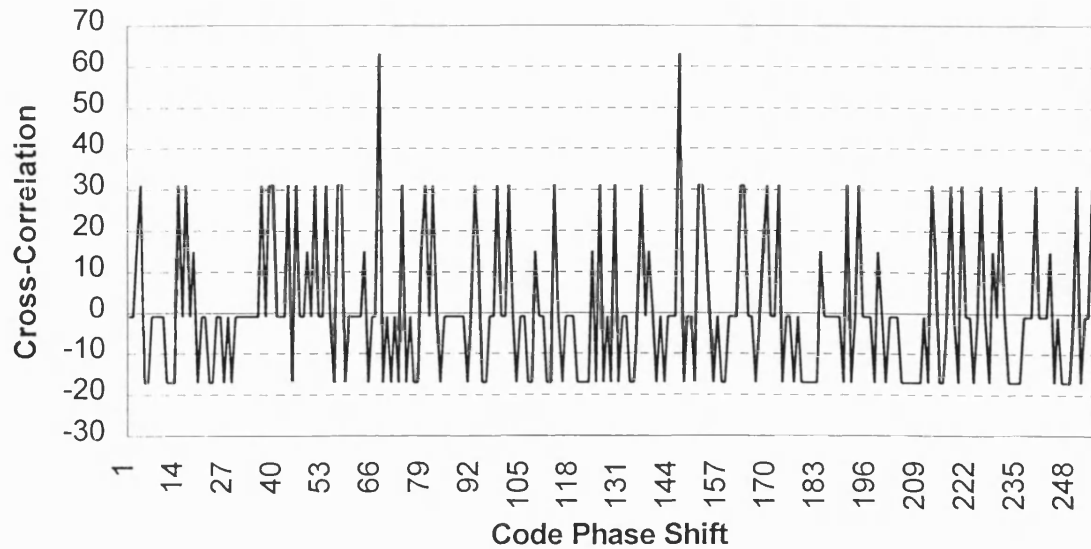
Figure A. 4: Periodic Cross-Correlation Function (PCCF) of a 255-chips ML sequence.

Although it is possible to select a subset of ML sequences that have relatively smaller cross-correlation peak value, but the number of signature codes in the set is usually too small. Therefore, as a multiple-access signature code set, the ML sequences do not provide enough capability for practical DS-CDMA systems [A- 1].

A.3 Gold Sequences

Gold sequences are the most widely known and used DS-CDMA signal designs [A- 2], [A- 5]. They have been derived from the fact that certain pairs of the ML codes with length N exhibit a three-valued periodic cross-correlation function with values $\{-1, -t(n), t(n)-2\}$, where $t(n)$ is defined as below:

$$t(n) = \begin{cases} 2^{(n+1)/2} + 1 & (odd\ n) \\ \\ 2^{(n+2)/2} + 1 & (even\ n) \end{cases} \qquad (A-7)$$

For example, if $n=8$ then $t(8)=2^5+1=33$ and the three possible values of the cross-correlation function are $\{-1, -33, 31\}$. Two ML sequences of length N with a periodic cross correlation function that takes one of the possible values $\{-1, -t(n), t(n)-2\}$, are called preferred pair.

Gold [A- 2] suggested the combining of two preferred pairs of ML sequences with the same period, to produce a set of DS-CDMA signature codes with cross-correlation properties as the original signature sequences. In this way, two preferred pairs, say $a=[a_1 a_2 \dots a_N]$ and $b=[b_1 b_2 \dots b_N]$, are used by taking the modulo-2 sum of a with the N cyclically shifted version of b. The set of derived sequences from preferred pair including the original preferred pair is known as the Gold sequences. Figure A. 5 shows the generation processing of the Gold sequences and Figure A. 6 shows the frequency spectrum of a 255-chip Gold sequence. Including two original components of ML signature sequences, a family of the Gold code set contains 2^n+1 sequences.
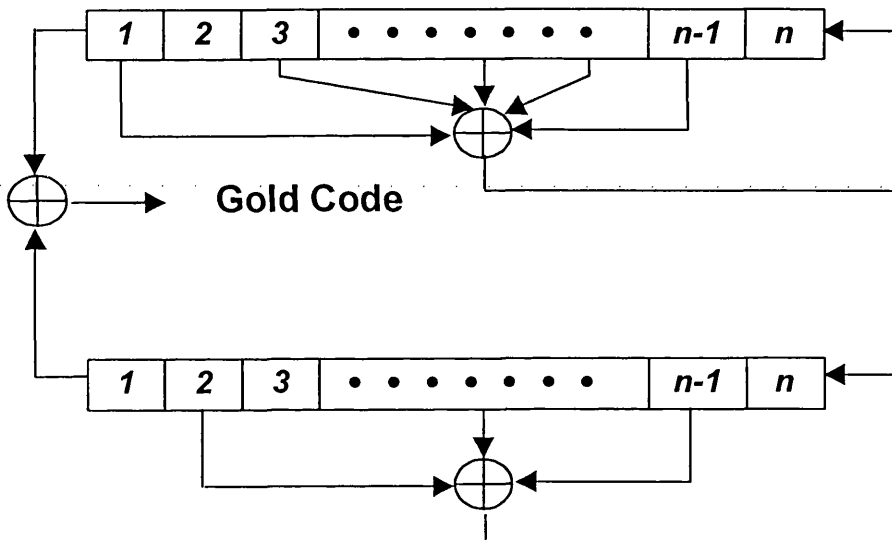
Figure A. 5: The process of generating the Gold sequences.
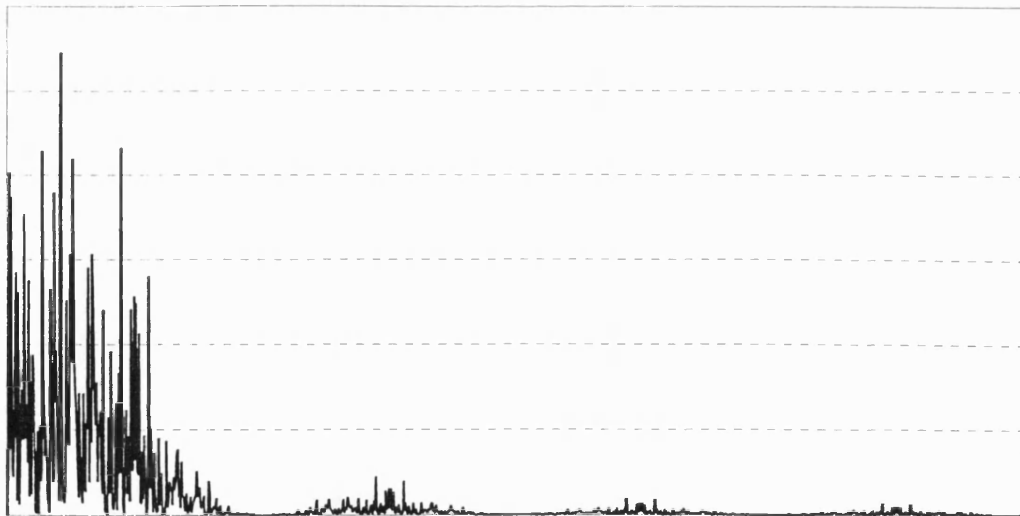
Figure A. 6: Frequency spectrum of a 255-chip Gold sequence.

Figure A. 7 shows the PACF of a 255-chip Gold sequence, which has been obtained via computer simulation. As it can be seen, a Gold sequence is characterised by an approximately flat periodic auto-correlation side-lobes that provides approximation for the ideal short spreading sequence for use in the DS-CDMA systems.
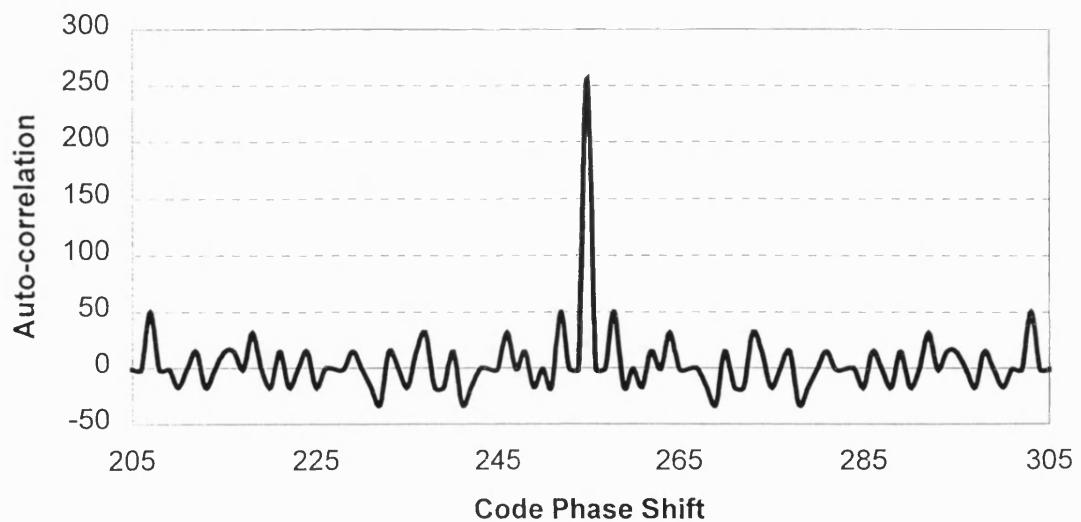
Figure A. 7: Periodic Auto-Correlation Function (PACF) of a 255-chips Gold signature code.

The PCCF of a 255-chip Gold sequence, which has been obtained via computer simulation, is shown in Figure A. 8. It can be seen that the cross-correlation function between any pair of Gold sequences of the same period is relatively better than the cross-correlation function between any pair of ML sequences and hence they are more acceptable for use in the DS-CDMA applications.
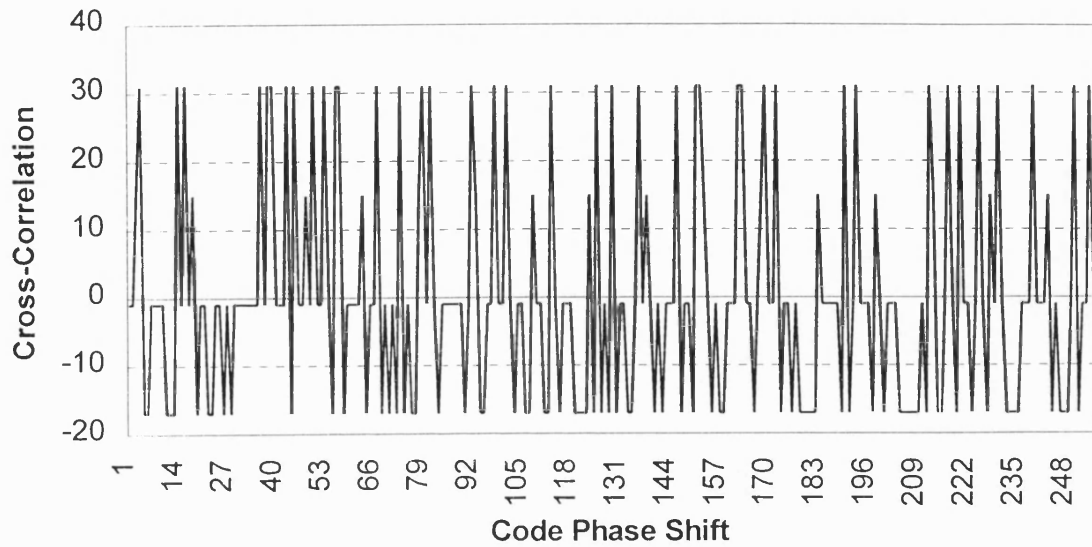
Figure A. 8: Periodic Cross-Correlation Function (PCCF) of a 255-chips Gold signature sequence.

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Appendix B

Multipath Channels in Mobile Communication

B.1 Introduction

The mobile radio propagation channel is the physical medium that supports electromagnetic wave propagation between a transmitter and a receiver. Due to the multiple reflections and diffraction produced by obstacles in the transmission medium, the transmitted signal follows a number of different paths before arriving at the receiver's antenna [B- 1]. The effects of each path on the transmitted signal are attenuate, delay and phase shift. At the receiver's antenna, a voltage is produced that represents a superposition of these scaled and phase shifted echoes of the transmitted waveform. Scatters, such as, hills, buildings and vehicles in the vicinity of a mobile unit can create reflected and diffracted waves, which are copies or echoes of a single propagating wave. An example of such a situation is shown in Figure B. 1.
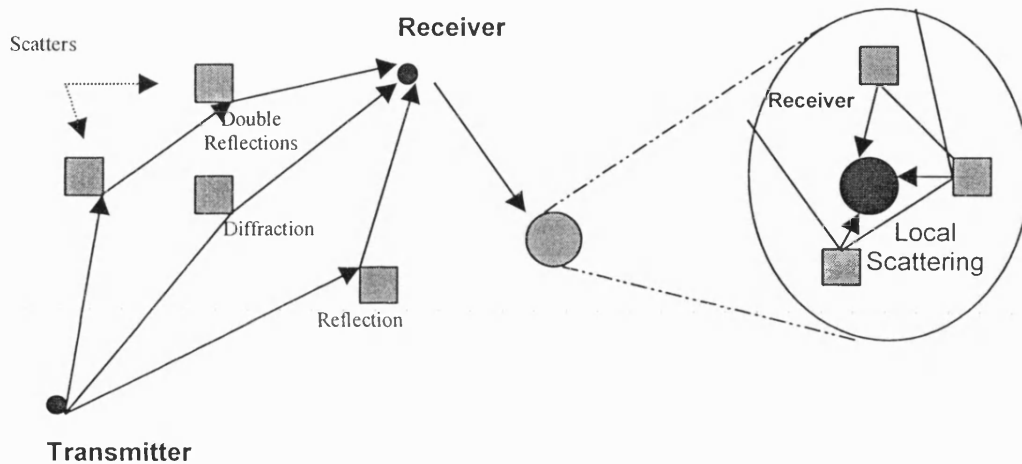
Figure B. 1: Reflection and diffraction effects in a multipath channel.

The simplest case of the multipath channel is the "static multipath", in which the transmitter and receiver are stationary. Figure B. 2 shows a simple example of the effect of a 2-ray static multipath channel on the transmitted signal. It can be seen that in this case, the transmitted signal in the receiver has been changed via passing through multipath channel.
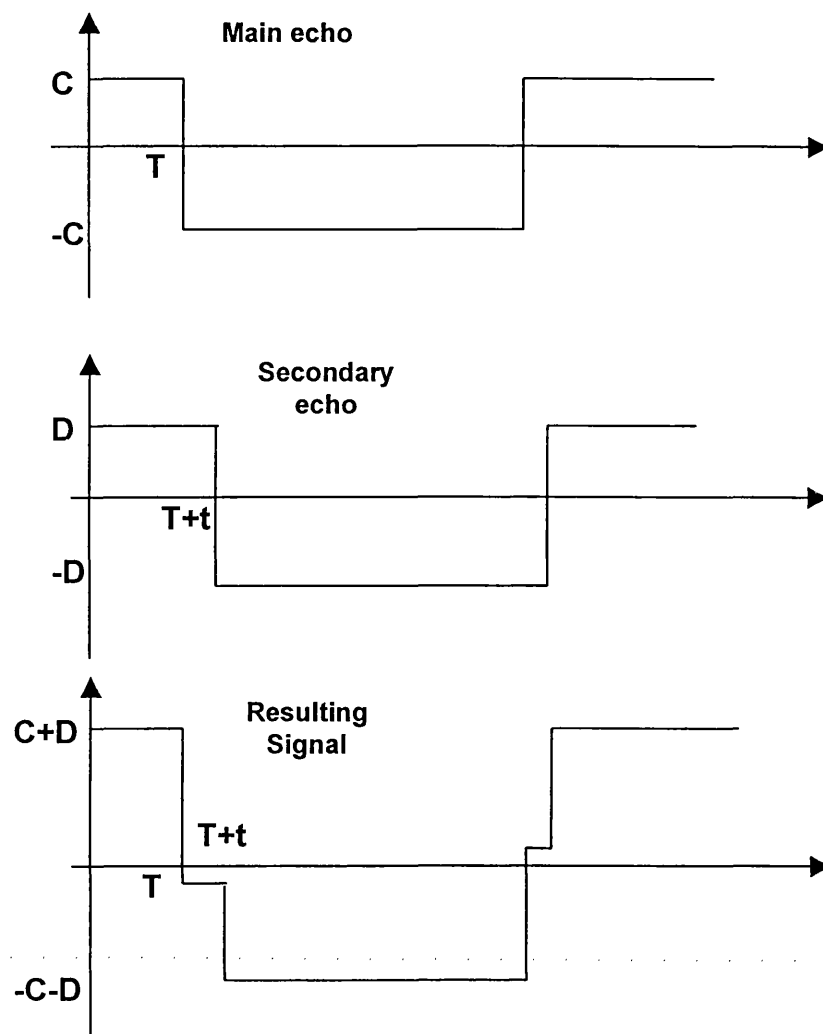
Figure B. 2: The effect of static multipath channel on the transmitted signal.

In a mobile channel, the transmitter or the receiver will be in motion and this causes the dynamical behaviour of the multipath channel. In this case and in the "dynamic multipath", the electrical length of every propagation path and the relative phase are changing continuously. This phenomenon affects the envelope of the signal in the channel, which at some positions has additions, and at other positions has cancellation. An example of changing the envelope of the received signal in a dynamic multipath channel is shown in Figure B. 3.
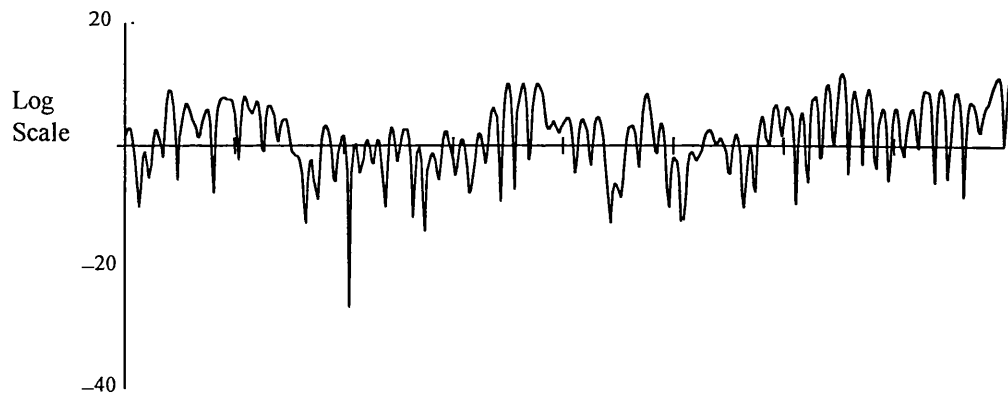
Figure B. 3: The effect of dynamic multipath channel on the envelope of the transmitted signal.

The effect of multipath channel on the amplitude and phase of the transmitted signal are known as fading. Two models of this phenomenon are known as fast fading and slow fading. The short-term fluctuation, which is caused by the local multipath, is the source of generating fast fading. This affects the instantaneous BER performance of the receiver. Slow fading is the average value of the envelope of the received RF signal.

To evaluate the behaviour of the multipath channel, "time delay spread" of the multipath and the "coherence time" of the channel are two important parameters. The delay spread is the duration of time between the first received signal and the last significant one and it may be from $5\,\mu\sec$ to $17.2\,\mu\sec$ for a typical urban and hilly terrain environment [B- 2]. The channel coherence bandwidth can be measured as the reciprocal of the delay spread [B- 3]. The coherence time of the multipath channel can be defined as the duration of time that the impulse response of the channel is relatively constant. It has a range from a few msec for outdoors-mobile channel, to a few hundred msec for indoor-mobile channel. The coherence time is related to the Doppler effect that appears because of mobility of the mobile unit. The reciprocal of the Doppler (frequency) spread is a measure of the coherence time of the channel [B- 3].

B.2 Multipath Channel Impulse Response

The transient behaviour of the multipath channel can be considered in the impulse response of the channel. In the ideal case, a line-of-sight transmission channel has an impulse response that is in the form of shifted impulse. The location and the amplitude of the shifted impulse show

the delay and the attenuation in channel. In real situation, the impulse response is a continuous waveform that contains various peaks corresponding to the major reflectors in the transmission channel. If the time axis is divided into time slots of equal sizes, each time slot contains a number of received signals corresponding to different paths whose arrival times are within the time slot. The impulse response of a multipath channel can be written as below:

$$h(\tau;t) = \sum_i \alpha_i(t) e^{-j\theta_i(t)} \delta(\tau - T_i) \qquad \text{(B-1)}$$

In equation **(B-1)**, $h(\tau;t)$ is the time varying impulse response of the multipath channel, $\delta(.)$ is the delta function, T_i is the excess delay of the ith multipath signal, $\alpha_i(t)$ is the attenuation of the ith multipath signal and $\theta_i(t)$ is the phase of the ith multipath signal that is equal to:

$$\theta_i(t) = 2\pi f_c \tau_i(t) \qquad \text{(B-2)}$$

As an example, Figure B. 4 and Table B. 1 show a set of wide-band channel impulse responses, specified by the Group Special Mobile (GSM) committee, describing typical urban and hilly terrain environments [B- 2].

B.3 Frequency Selective Rayleigh Fading Channels

To evaluate the performance of different receivers in the DS-CDMA environment, the wide-band multipath-fading channel should be implemented as the transmission environment. The wide-band propagation multipath channel is the superposition of a number of dispersive paths. These paths have various attenuation, delays and Doppler shifts. This type of channel can be modelled by using a tapped delay line with K taps as shown in Figure B. 5 [B- 4].

Urban Channel Impulse Response

Hilly Terrain Channel Impulse Response
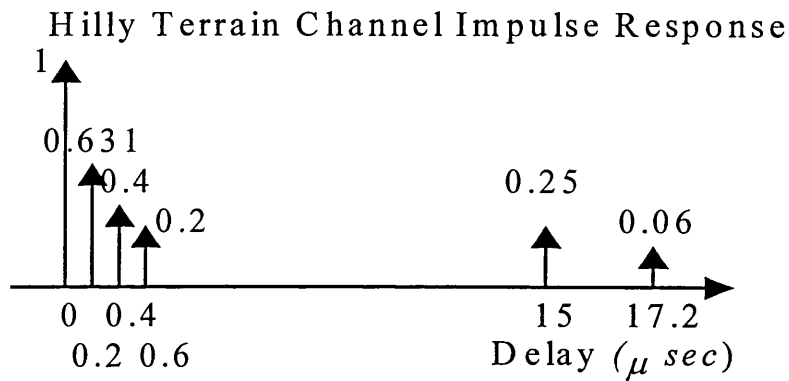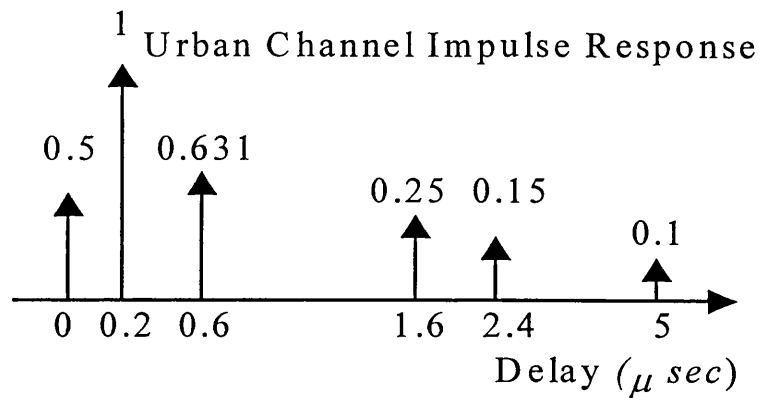
Figure B. 4: A set of wide-band channel impulse responses.

Path (Urban)	1	2	3	4	5	6
Delay (μsec)	0.0	0.2	0.6	1.6	2.4	5
Gain (dB)	-3.0	0.0	-2.0	-6.0	-8.0	-10.0

Path (Hilly)	1	2	3	4	5	6
Delay (μsec)	0.0	0.2	0.4	0.6	15	17.2
Gain (dB)	0.0	-2.0	-4.0	-7.0	-6.0	-12.0

Table B. 1: Six-tap multipath channel option for urban and hilly terrain environments.

210
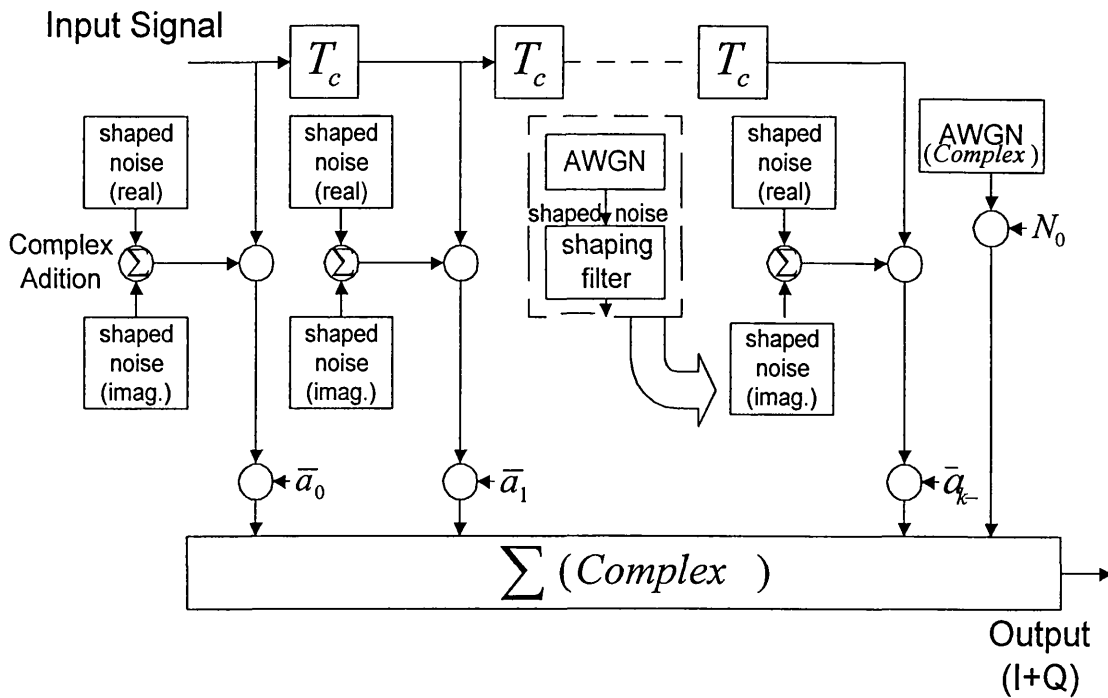
Input Signal

Figure B. 5: The channel simulator model.

The base-band signal is applied to a series of delays equal to the width of the chip period. The output signal from each tap is multiplied by a time varying coefficient for generating the fast fading channel. The Doppler effect is added by shaping the AWGN using a classical Doppler filter. A cascade structure of two-second order filters is employed to approximate the frequency domain transfer function of the Doppler filter. The transfer function of this cascaded filter is:

$$H(s) = \frac{1}{s^2 + \sqrt{2}s + 1} \frac{1}{s^2 + 0.02s + 1} \tag{B-3}$$

To implement the cascaded filter in the discrete domain, it requires having a transformation from the Laplace domain into the z-domain. This transformation can be obtained by using the Bilinear Z-Transform as below:

$$H(z) = \frac{0.014 \cdot (1 + 2z^{-1} + z^{-2})}{1.1814 - 1.972z^{-1} + 0.8466z^{-2}} \cdot \frac{0.014 \cdot (1 + 2z^{-1} + z^{-2})}{1.0163672 - 1.972z^{-1} + 1.0116328z^{-2}} \tag{B-4}$$

The frequency response of the cascaded filter at a Doppler frequency of 40 Hz is shown in Figure B. 6.
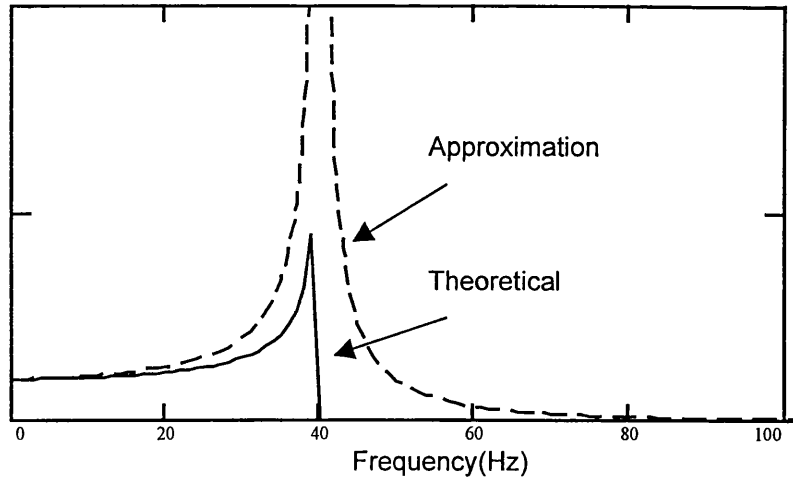
Figure B. 6: The frequency response of a Doppler filter at a frequency of 40 Hz.

The shaped noise is obtained by passing the AWGN via the Doppler filter and it can be shown that the Rayleigh fading is produced at the output of the shaping filter because of independent Gaussian fading on both the real and the imaginary weighting components. To implement the static multipath channel, fixed weighting factors are used for each tap in the channel model. A further gain, which shows the average multipath signal strength expected at that delay, is multiplied by the signal in the output of each shaping filter in the model and finally, the output signal of all taps are added by using a complex summer.

The Doppler fading is characterised by shaping filter that is tuned to the Doppler frequency $f_d = f_c \cdot \frac{v}{c}$. In this case, f_d is Doppler frequency, f_c is the carrier frequency, v is the vehicle speed and c is the speed of electromagnetic propagation in free space. The noise shaping filter is a second order biquadratic filter that determines the rate and type of fading [B- 4]. Figure B. 7 shows the frequency response of the shaping filter.
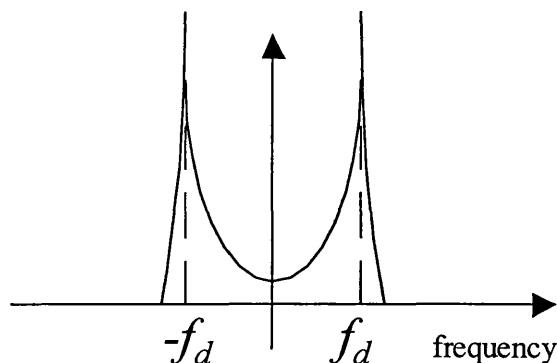
Figure B. 7: Frequency response of the shaping filter.

B.4 Estimating Techniques of the Multipath channel's Impulse Response

The impulse response of the mobile channel in a DS-CDMA environment can be determined by taking the cross-correlation of the received signal and the local PN signature waveform. In the line-of-sight transmission mode, the estimated result should be an impulse function that its location determines the delay in the transmission channel. In the multipath channel, there is more than one impulse in the impulse response of system that indicates different paths of channel for signal propagation.

Figure B. 8 shows the structure of a DS-CDMA multipath channel estimator. In this structure, the received signal after correlating with the appropriate delayed versions of the PN sequence, is integrated over a bit period, T_b. It is assumed that the relative delay between each echo is T_c, where T_c is a chip period. The correlator estimates the amplitude and phase values of the multipath channel's impulse response.
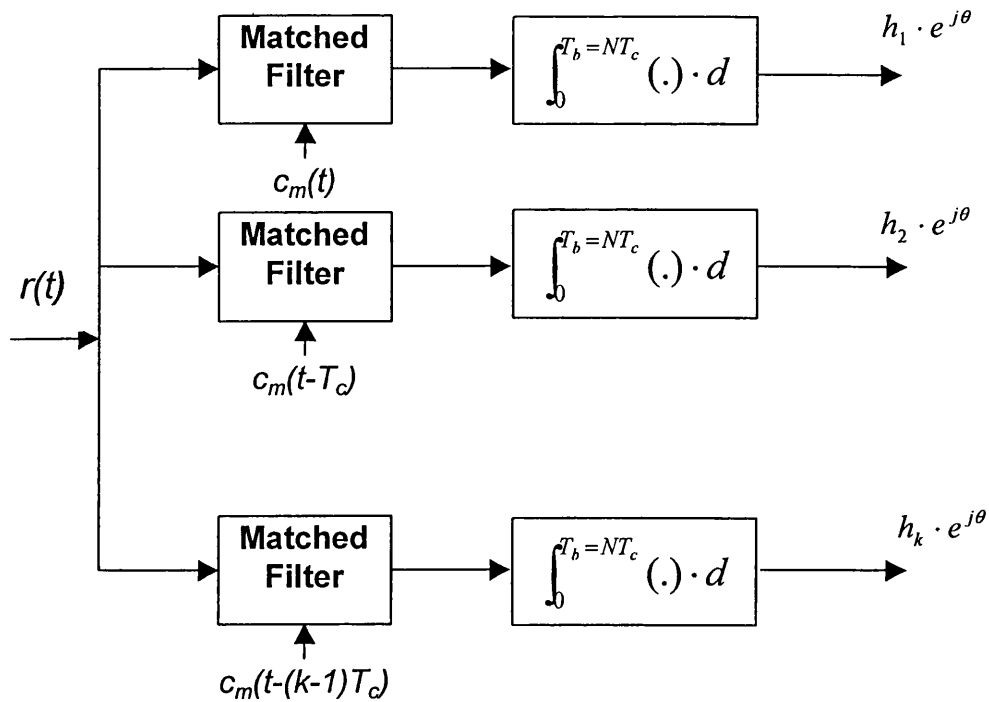
Figure B. 8: The structure of the DS-CDMA multipath channel estimator.

The DS-CDMA multipath channel estimator introduces a delay in the estimation of one bit period T_b. This is the time that the correlator requires calculating the cross-correlation of the received signal with the different delayed versions of local signature waveform. This means that the channel estimation obtained from the previous bit is applied to the current bit. It is also needed to remove the data content that is one of the functions made by the alpha tracker.

The estimation of the impulse response of the multipath channel, because of some reasons, is not always perfect. The first reason is that the result of correlating the PN sequence with itself is not a delta function and only approximates this waveform. Furthermore, the AWGN introduced by the channel and co-channel interfering user's signals, decreases the accuracy of the estimation. To improve the performance of the multipath channel estimating process and to implement a suitable receiver to combat the effect of DS-CDMA multipath channel, some combination techniques can be implemented. Equal Gain Combination (EGC) and Maximum Ratio Combination (MRC) are two most famous techniques in this area [B- 4].

B.4.1 EGC Combining Technique

In the EGC technique, there are only four possible weights, $\pm 1 \pm j$, for each multipath component. It means that only the sign of real and imaginary part of the complex estimated parameters are employed to determine the multipath channel impulse response. In this case, it is assumed that all paths in the multipath channel have identical effect on the transmitted signal. The EGC combination technique can be demonstrated by equation **(B-5)**.

$$
\begin{aligned}
h_k(n)_I &= Sgn\!\left[b_{n-1} \cdot x_k(n-1)_I\right] \\
h_k(n)_Q &= Sgn\!\left[b_{n-1} \cdot x_k(n-1)_Q\right]
\end{aligned}
\tag{B-5}
$$

In this equation, Sgn(.) is the sign function, $x_k(n)$ is the kth post-correlated sample for the nth bit, $h_k(n)$ is the estimated channel coefficient for the nth bit, and b_{n-1} is the $(n-1)^{th}$ decided bit.

B.4.2 MRC Combining Technique

In the MRC technique, the real and the imaginary part of the complex estimated parameters are employed to determine the multipath channel impulse response. In this case, it is assumed that each path in multipath channel has its effect on the transmitted signal. Equation **(B-6)** demonstrates the MRC combination technique.

$$
\begin{aligned}
h_k(n)_I &= b_{n-1} \cdot x_k(n-1)_I \\
h_k(n)_Q &= b_{n-1} \cdot x_k(n-1)_Q
\end{aligned}
\tag{B-6}
$$

In equation **(B-6)**, $x_k(n)$ is the kth post-correlated sample for the nth bit, $h_k(n)$ is the estimated channel coefficient for the nth bit, and b_{n-1} is the $(n-1)^{th}$ decided bit.

B.4.3 Alpha Tracker

In the dynamic multipath channel, the parameters of time varying channel should be tracked and updated. In this way, the tracker should be added to the estimator of the multipath channel. Two basic functions of the multipath signal trackers are:

♦ It must remove the data content on the post-correlated signal so that the fading signal (with noise) can be reconstructed.

♦ It must track the fading signal but reject the noise on the channel.

The tracking system isolates the individual estimated channel coefficients from the cross-correlation and tracks them independently after the data content has been removed. A fast-fading channel provides only a short period over which the tracker can learn the channel response before it changes significantly. The filter memory must allow a reasonable amount of averaging to provide a usable SNR. This can be formulated by applying the constraint that the channel must have a Doppler frequency, f_d, of much less than the data rate.

For the MRC technique, a simple alpha tracker [B- 4] can be employed to improve the performance of channel estimator. It is because, the MRC requires a short time window to form an estimate. Separate alpha trackers are employed to estimate the in-phase and the quadrature components of the complex parameters of the multipath channel impulse response. The MRC technique with alpha tracker can be explained as below:

$$h_k(n)_I = (1-\alpha) \cdot b_{n-1} \cdot x_k(n-1)_I + \alpha \cdot h_k(n-1)_I$$
$$h_k(n)_Q = (1-\alpha) \cdot b_{n-1} \cdot x_k(n-1)_Q + \alpha \cdot h_k(n-1)_Q$$

(B-7)

In equation (B-7), α is the parameter that determines the rate of changing in the tracker and its value is $0 < \alpha < 1$.

The optimum value of alpha depends on the SNR of the received signal. It is shown that for alpha equal to 0.5, the lowest BER is obtained in the suitable receiver [B- 4]. In general, it can be said that when alpha is chosen low, the estimation result is more effected by the noise of the received signal. When alpha is set to be high, close to one, the noise can be cancelled effectively but the estimator can not follow the fast variations of the multipath-fading channel.

In summary, Although the EGC type of combining has lower complexity than the MRC, it offers lower performance than the MRC [B- 4]. The MRC takes into account the mean SNR of each multipath components and then combine them coherently. The EGC gives the same gain to all components while the MRC enhances the high power components.

B.5 References

[B- 1] B. Sklar, " Rayleigh Fading Channels in Mobile Digital Communication Systems," *IEEE Communications Magazine,* pp. 90-111, Jul. 1997.

[B- 2] R. Steele, " *Mobile Radio Communications,*" IEEE Press, New York, 1992.

[B- 3] J. G. Proakis, " *Digital Communications,*" 3rd ed., New York: McGraw-Hill, 1995.

[B- 4] G. J. R. Povey, P. M. Grant and R. D. Pringle, " A Decision-Directed Spread Spectrum RAKE Receiver for Fast Fading Mobile Channels," *IEEE Trans. on Vehicular Tec.*, Vol. 45, No. 3,pp. 491-502, Aug. 1996.

Appendix C

Software Validation

C.1 Introduction

In this Appendix, some results from independents published papers in the form of graphs are presented. These graphs are used to validate the simulation software that has been used for to produce the results in this thesis.
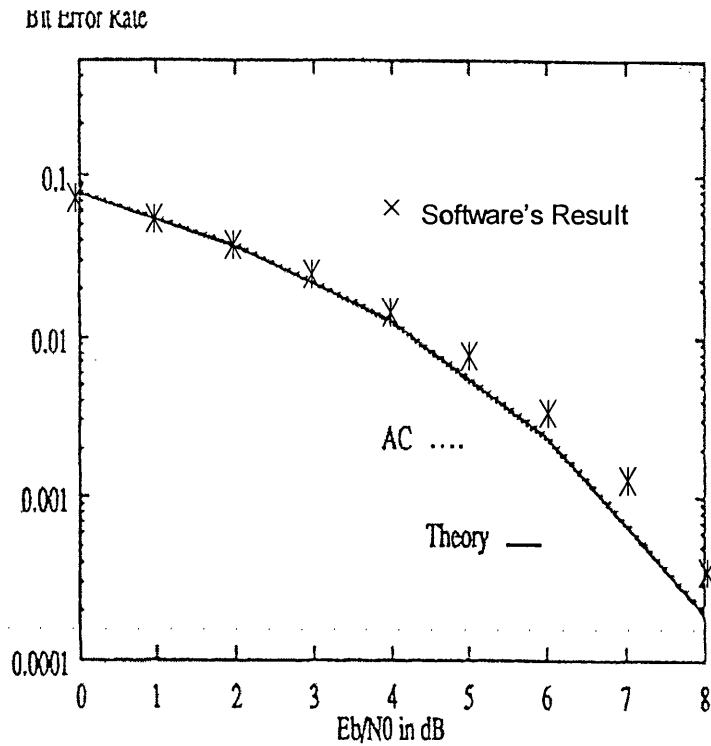
Figure C. 1: 31 Chip BER: Adaptive MMSE Correlator (AC) Receiver and RAKE Receiver [C- 1].

N=31 case

SNR1
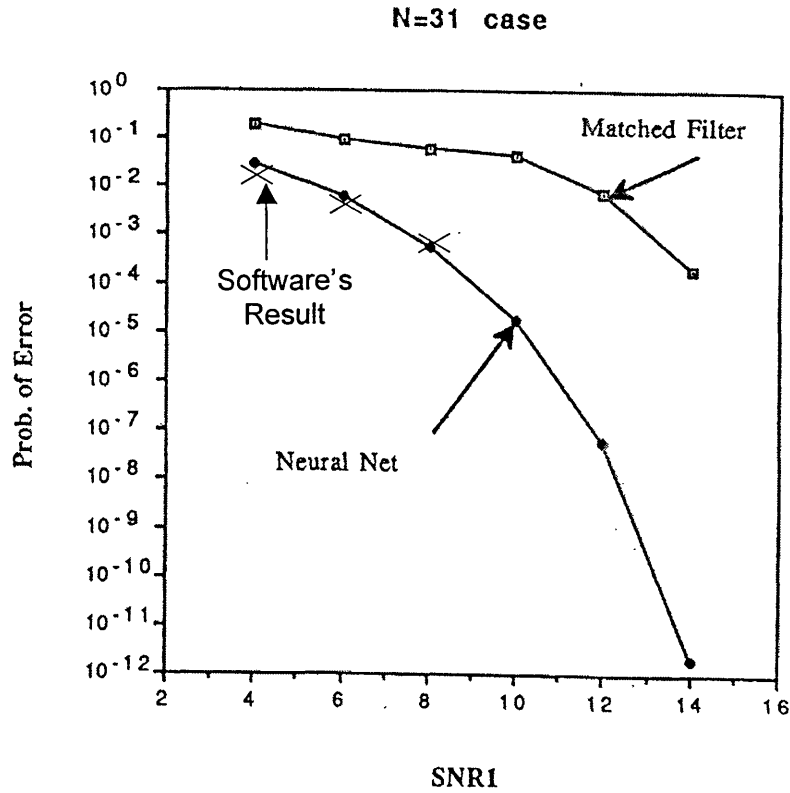
Figure C. 2: Average error probability versus signal-to-noise-ratio of user 1 for an asynchronous two-user Gaussian channel with E_2/E_1 =6 dB and N=31 [C- 2].
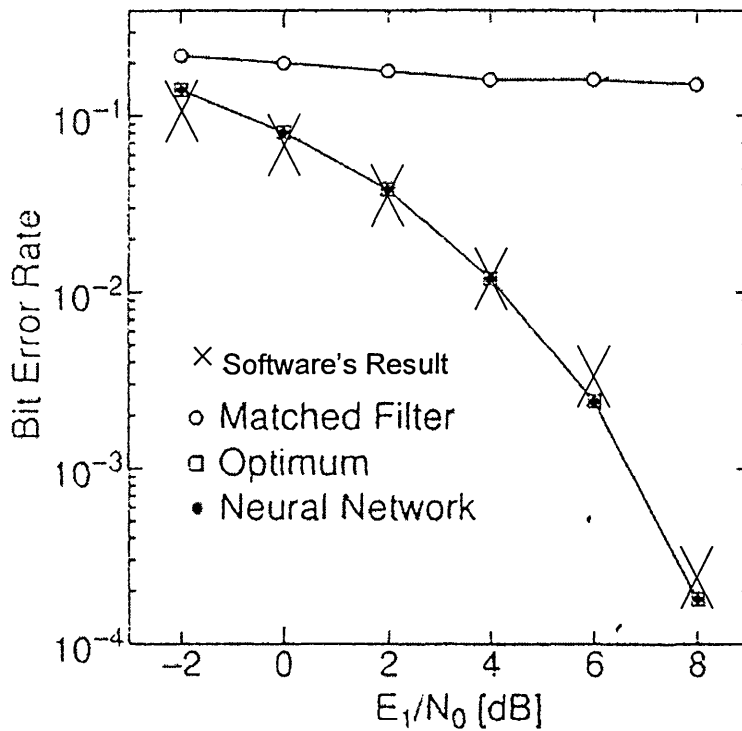
Figure C. 3: Bit error rate versus E_1/N_0 for a six-user channel with E_i/E_1 =6 dB [C- 3].

C.2 References

[C- 1] C. N. Pateros and G. J. Saulnier, " An Adaptive Correlator Receiver for Direct-Sequence Spread Spectrum Communication," *IEEE Trans. on Communications,* Vol. COM-44, No. 11, pp. 1543-1552, Nov. 1996.

[C- 2] B. Aazhang, B. Paris, and G. C. Orsak, " Neural Network for Multi-User Detection in Code-Division Multiple-Access Communications," *IEEE Trans. on Communications,* Vol. COM-40, No. 7, pp. 1212-1222, July 1992.

[C- 3] T. Miyajima, T. Hasegawa, and M. Haneishi, " On the Multi-User Detection Using a Neural Network in Code-Division Multiple-Access Communications," *IEICE Trans. on Communications (Japan),* Vol. E76-B, No. 8, pp. 961-968, August 1993.

Appendix D

Publications

An Adaptive DS-CDMA Receiver for Multipath and Multi-User Environments

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Abstract-A major limitation to the capacity of direct-sequence code division multiple access systems is multiple access interference produced by the other co-channel users. The optimum multi-user detector is currently too complex to be implemented in commercial systems. In this paper, an adaptive minimum mean square error (MMSE) receiver is introduced which can combat the 'near-far' problem and reject multi-user interference in a multipath-fading channel. This type of channel is subject to rapid deep fades and the receiver's performance can be severely degraded by the limited convergence speed of the adaptive algorithm. Here, an equaliser is used to improve the ability of an adaptive MMSE receiver to combat the effect of the multipath fading. Maximal ratio combining (MRC) and an alpha tracker is used to estimate the impulse response of the multipath channel. Results show this technique is effective for rejecting multiple access interference in a multipath-fading channel.

I. INTRODUCTION

DS-CDMA is attractive for wireless multiple-access communications because of its ability to gain diversity from multipath signals and because in a cellular radio system it allows universal frequency re-use. These characteristics increase the capacity of CDMA over other multiple access techniques and offer other important system advantages. Multiple access interference (MAI) produced by the other co-channel users is a significant limitation to the capacity of conventional CDMA systems however.

A potential solution to this problem is the optimum multi-user detector consisting of a bank of matched filters followed by a Viterbi maximum-likelihood (ML) detector [1]. The computational complexity of this detector increases exponentially with the number of users and it is currently too complex to implement in commercial systems. Consequently, a number of sub-optimal multi-user detectors have been proposed recently [2-9]. These detectors can achieve significant performance gains over the conventional (non-MAI-cancelling) detector without the exponential increase in complexity as the num-

ber of users increases. However, their performance depends on knowing various parameters such as the received signal amplitude, the timing of user transmissions relative to other users, and the cross-correlation of signature codes. This information may be available to a base station but it is not readily available to the mobile units and this can compromise the system performance. In addition, in a multipath environment, there is no prior knowledge of the timing of the delay paths for all the received signals.

One way of dealing with multipath signals is to use diversity-combining techniques. Space diversity can be implemented in the base station but in mobile units, because they are portable, this is not desirable. Direct-sequence spread-spectrum modulation offers inherent time diversity, depending on the chip-duration relative to the delay-spread. Consequently, the RAKE receiver is a well-known technique for resolving and combining multipath signals in DS-CDMA systems. Although it is known that a reasonable performance can be achieved in the presence of multipath signals by the RAKE receiver [10], MAI is the main factor for degrading the performance of this type of receiver.

Another important development in the improvement of the performance of DS-CDMA receivers, particularly for the mobile handset, has been the design of adaptive detectors, that 'self-tune' the detector parameters from the observation of the received signal [11]. Studies of adaptive receiver structures by Madhow and Honig [12,13], Miller [14,15], and Pateros and Saulnier [16] have shown that this type of receiver has a measure of 'near-far' resistance and can produce significant performance improvements in the presence of MAI, multipath channels and narrow band interference. However, they do not operate particularly well in fast fading because the adaptation speed is too slow to allow tracking of the fast varying channel. This problem has been addressed by Miller [17] who investigated the behaviour of the MMSE receiver in flat fading and

proposed a modification for combating the effect of losing phase lock of the desired user in deep fades.

In this paper, a modified version of a low complexity adaptive MMSE receiver for a direct-sequence CDMA system [14] is presented. The new system has an improved performance that allows it to operate in multipath fading channels. This receiver is able to despread the desired signal, reject the MAI, and combat the effect of multipath fading. The simplicity of the receiver makes it attractive for use in both the base-station and the mobile handset.

II. MODEL OF AN ASYNCHRONOUS CDMA SYSTEM

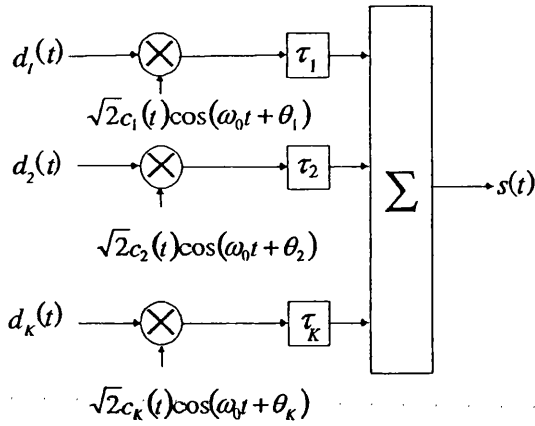The block diagram of an asynchronous CDMA system is shown in figure 1.

Fig. 1: Asynchronous phase-coded CDMA model.

The system model consists of K simultaneous users. Each user is assigned a unique signature waveform. The kth user's signature is $c_k(t)$ and consists of bipolar rectangular pulses of period NT_c, where T_c is the chip period, N is the length of the code, such that $N = T_b/T_c$, and T_b is the data bit period. The kth user's transmitted signal is:

$$s_k(t) = \sqrt{2}d_k(t)c_k(t)\cos(\omega_0 t + \theta_k) \qquad (1)$$

where $d_k(t)$ is the polar data with amplitude ± 1 and duration T_b. The transmitted signal is of the form:

$$s(t) = \sum_{k=1}^{K} s_k(t - \tau_k) \qquad (2)$$

In (2), τ_k is a random integer that has a uniform distribution over $(0, T_b)$. The received signal in an AWGN channel is of the form:

$$r(t) = \sum_{k=1}^{K} \sqrt{P_k}\, s_k(t - \tau_k) + n(t) \qquad (3)$$

where P_k is the received power of the kth user's signal and $n(t)$ is the noise signal. In a multipath channel of impulse response, $h_d(\tau;t)$, the desired user's received signal is [10]:

$$r_d(t) = s_d(t - \tau_d) * h_d(\tau;t) + n(t) \qquad (4)$$

where

$$h_d(\tau;t) = \sum_{i=0}^{L-1} a_i(t)e^{-j\theta_i(t)}\delta[\tau - iT_c] \qquad (5)$$

In (5), L is the number of signal paths, each assumed to be spaced with a delay of T_c, $a_i(t)$ is the amplitude of the ith multipath signal, $\theta_i(t)$ is the phase of ith multipath signal, and iT_c is the excess delay of the ith multipath signal, relative to the line of sight delay.

III. THE MMSE ADAPTIVE RECEIVER

Figure 2 shows the structure of the MMSE detector. After converting the received signal to baseband, it is passed through a chip matched filter and sampled at the end of every chip interval. These samples are fed into the channel equaliser that removes the effect of multipath fading channel on the desired user's signal. The impulse response of the equaliser is the complex conjugate of the multipath channel's impulse response. After that, the signal is fed into the adaptive finite impulse response (FIR) transversal filter. The number of taps in the transversal filter is equal to the period of the signature waveform. The output of the filter in our simulations is sampled once every bit interval and hard-limited to form the estimate of the received data. The tap weights are updated once every bit interval and an error signal that is the difference between the desired signal and the output of the adaptive filter controls the updating process. A least mean square (LMS) adaptive algorithm is used.

$$(1)$$

In this system, if the desired signal were received in the presence of AWGN only, it would have optimum performance. When there is also MAI present, the adaptive nature of the receiver changes the coefficients of the filter in the sense of minimum mean square error to reduce the interference and noise. The performance of the adaptive MMSE receiver in multipath fading channel with Doppler depends on the convergence speed of the adaptive algorithm.
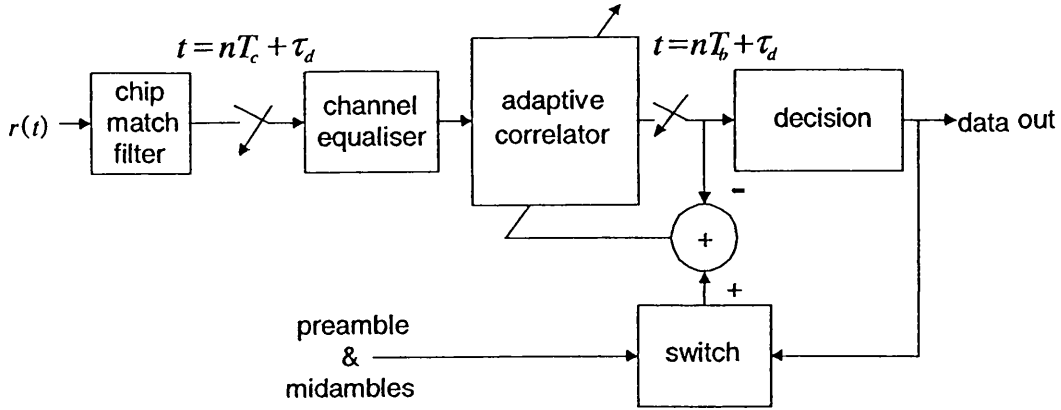
Fig. 2: The structure of the adaptive MMSE receiver.

Increasing the step size parameter, μ, in the LMS algorithm can increase the ability of the receiver to combat the effect of fast fading but the stability of the receiver decreases and the BER of receiver may well increase. In this situation, there are benefits in using a channel equaliser before the adaptive MMSE receiver to combat the effect of the multipath-fading channel.

IV. MULTIPATH CHANNEL ESTIMATION

One possible method of determining the channel impulse response is from the cross-correlation between the received signal and the signature waveform of desired user. This method of estimating the channel impulse response is not perfect because the auto-correlation of the signature waveforms is not a perfect delta function. In addition, the MAI and AWGN introduced by the channel decrease the accuracy of the estimation.

A better technique is to use maximum-ratio combining (MRC), which can be used with a simple alpha tracker [10]. This algorithm requires a short time window to form an estimate and has low complexity. Separate alpha trackers are used to estimate the in-phase and quadrature components of the channel impulse response:

$$h_k(n)_I = (1-\alpha) \cdot b_{n-1} \cdot x_k(n-1)_I + \alpha \cdot h_k(n-1)_I$$
$$h_k(n)_Q = (1-\alpha) \cdot b_{n-1} \cdot x_k(n-1)_Q + \alpha \cdot h_k(n-1)_Q \quad (6)$$

where $x_k(n)$ is the kth post-correlation received sample for bit n, $h_k(n)$ is the estimated channel coefficient for bit n, b_{n-1} is the previous decided bit and $0<\alpha<1$. The optimum value of alpha depends on the SNR of the received signal. The complex conjugate of the estimated impulse response is used to equalise the channel.

V. SIMULATION AND RESULTS

To verify the ability of the adaptive MMSE receiver to combat the effect of the multipath-fading channel and reject the MAI, the adaptive receiver of figure 2 with 31 complex tap weights was simulated. The tap weights were tuned by using the complex normalised LMS algorithm during training and data sequence transmission. The spreading sequences for all users were chosen from a Gold set of length 31 chips and BPSK modulation was used for all users. The relative clock offset, τ_k, for each of the users was chosen randomly from a uniform distribution. For comparison, a conventional RAKE system was also simulated.

The channel model is a tapped delay line of six taps, which are spaced according to the GSM channel impulse response. It is assumed that the carrier frequency is 900 MHz and the chip rate of the signal is 3.1×10^6 chips/sec and each delay space in channel model is approximately 0.2 μsec. The complex valued output from each tap is multiplied by the time varying Rayleigh distributed coefficients that characterise the fading channel. It is then multiplied by a further gain, which represents the average multipath signal strength expected at that delay. The weighting factors are chosen from the COST207 urban impulse response model, given in Table 1. The mobility of the user is incorporated into the channel using Doppler filters which filter the Rayleigh distributed noise representing the path loss.

Path	1	2	3	4	5	6
Delay (μsec)	0.0	0.2	0.6	1.6	2.4	5.0
Gain (dB)	-3	0	-2	-6	-8	-10

Table 1: Coefficients of the urban channel model

Figure 3 shows the BER characteristics of both the new adaptive MMSE receiver and the RAKE receiver in a known multipath-fading channel for an 80 Hz Doppler frequency. As can be seen, in this situation, there is no significant difference between the performances of the two receivers.
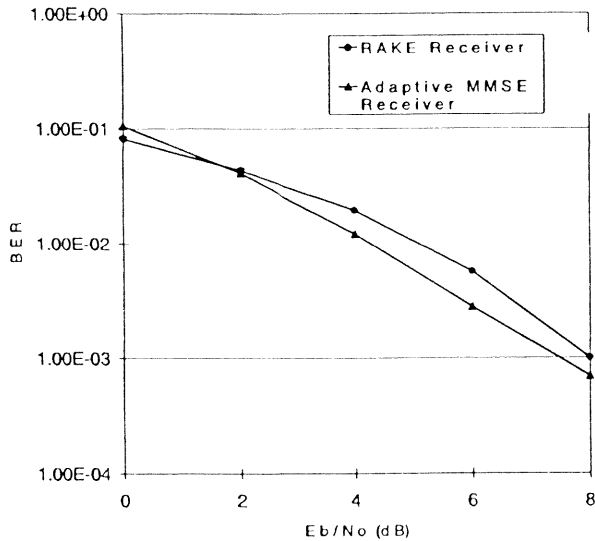
Fig. 3: BER of adaptive MMSE and RAKE receivers in a 6 ray COST207 Rayleigh fading channel (known channel response, f_d=80 Hz).

Figures 4 and 5, respectively, show the BER characteristics of the RAKE and the adaptive MMSE receivers in a known multipath-fading channel for an 80 Hz Doppler frequency and a multiple-access interference channel. It can be seen that the new adaptive MMSE receiver has an excellent performance for combating the effect of MAI.
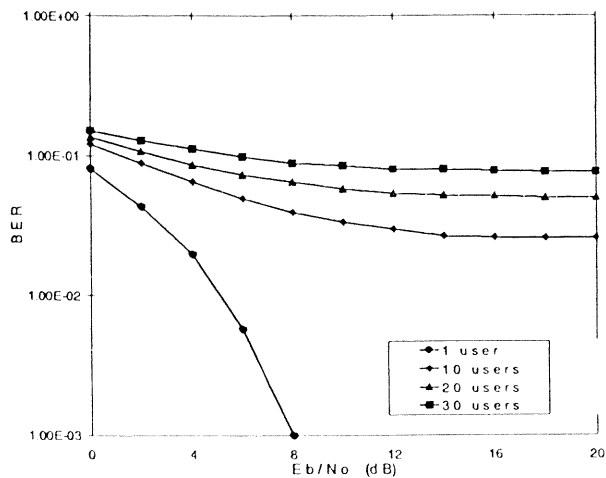
Fig. 4: BER of RAKE receiver in 6 ray COST207 Rayleigh fading channel (known channel) and MAI with power equal to desired user (NLMS algorithm, f_d=80 Hz).
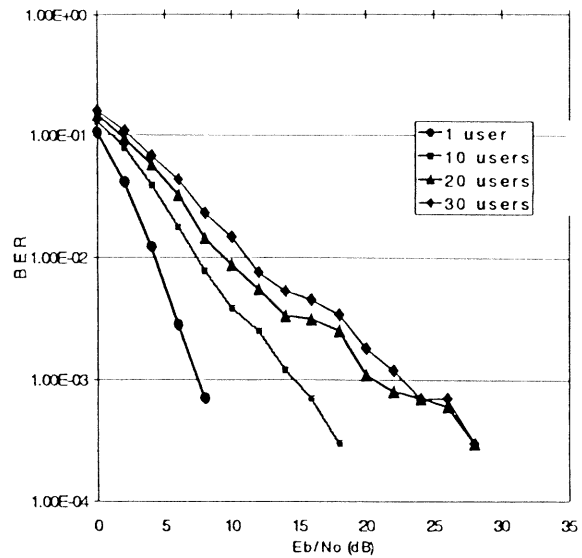
Fig. 5: BER of adaptive MMSE receiver in 6 ray COST207 Rayleigh fading channel (known channel) and MAI with power equal to desired user (NLMS algorithm, f_d=80 Hz).

In a real situation, it is necessary to estimate the channel impulse response and use this estimation to equalise the effect of the channel. To estimate the channel's parameters, we have used MRC [10] and the equalisation is performed by the complex conjugate estimate of channel's impulse response. Figure 6 shows the BER performance of the adaptive MMSE receiver with an MRC estimate of channel impulse response for the 6 tap COST207 Rayleigh fading channel.

Fig. 6: BER of adaptive MMSE receiver with MRC estimate of channel impulse response in a 6 ray COST207 Rayleigh fading channel and MAI with power equal to desired user (NLMS algorithm, f_d=80 Hz).

It is seen that this technique has a good performance in high E_b/N_0. However, this method for estimating the channel's characteristic is sensitive to the noise level in the channel.

VI. CONCLUSIONS

In a multipath-fading channel, the receiver's performance degrades because of the fast time-varying environment and the limited convergence speed of the adaptive algorithm and there is a trade off between the speed of convergence and the stability of the adaptive receiver. In this situation, we need to use an equaliser to combat the effect of time varying channel.

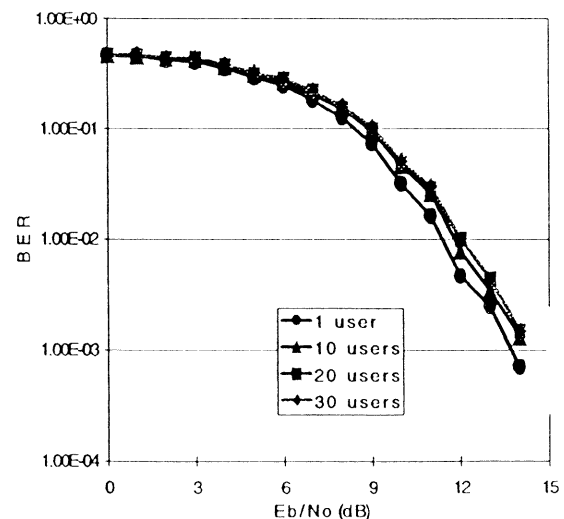The performance of the adaptive MMSE receiver in the multipath fading channel depends on a good estimate of the channel impulse response and equalisation of channel's effect on desired signal. In this way, Maximal Ratio Combining (MRC) is used to estimate the multipath fading channel's impulse response. The results show this technique is very effective for rejecting multiple access interference in the multipath fading channel but it is sensitive to the noise level and it's performance at high E_b/N_0 is better than at low E_b/N_0.

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AN ADAPTIVE NEURAL NETWORK RECEIVER FOR CDMA MULTI-USER INTERFERENCE CANCELLATION IN MULTIPATH ENVIRONMENTS

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ABSTRACT

The capacity of direct-sequence code-division multiple-access systems is severely limited by multiple access interference produced by the other co-channel users. To improve the capacity, joint-detection receivers and multi-access interference cancellation techniques have been proposed. Frequency-selective multi-path fading, however, has a significant effect on the performance of these types of receiver. This paper presents an adaptive neural-network-based receiver that has the capability of combating the 'near-far' problem and rejecting the multi-user interference in a multipath channel. A comparative performance analysis of the conventional matched-filter, a RAKE receiver and the adaptive neural network receiver is carried out using a Monte Carlo simulation. It is found that the new receiver performs extremely well as a sub-optimal receiver in multipath and multiple access channels with a significant 'near-far' effect.

INTRODUCTION

Direct-sequence code-division multiple-access (DS-CDMA) is attractive for wireless multiple-access communications because it allows complete frequency re-use in a cellular network. Other advantages of the CDMA method are 'soft-capacity' and 'soft-handoff'. However, multiple access interference (MAI) produced by the other co-channel users is a significant limitation to the capacity of conventional CDMA systems. A potential solution to this problem is the optimum multi-user detector that consists of a bank of matched filters followed by a Viterbi maximum likelihood (ML) detector [1]. The computational complexity of this detector increases exponentially with the number of users however, and the method is extremely complex to implement for a realistic number of users. As a consequence, there has been considerable research into sub-optimal detectors [2-9]. These detectors achieve significant performance gains over the conventional detector without the exponential increase in receiver complexity as the

number of users increases. However, their performance depends on prior knowledge of various parameters such as the received signal amplitude of each signal, their timing, and the cross-correlation performance of the signature codes. This information may be available to a base station but it is not readily available to the mobile units. Consequently, another important development in multi-user detection has been the design of adaptive detectors that 'self-tune' the detector parameters from the observation of the received signal [10].

Neural networks have been used for some time for the more general problem of interference rejection but it is only very recently that the method has been applied to MAI cancellation in CDMA receivers. The first paper that considered the application of neural network receivers to multi-user detection is due to Aazhang , Paris and Orsak [11]. They proposed a detection system that used a multi-layer neural network. Miyajima *et al* [12] proposed a Hopfield neural network for multi-user detection that uses the likelihood function as the energy function to be minimised.

In this paper, a feed-forward adaptive neural network receiver is considered for a DS-CDMA system and a comparative performance analysis of this system with a conventional matched filter receiver with RAKE combining is presented using a Monte Carlo simulation. It is found that the proposed receiver is able to despread the desired signal, suppress the effect of multipath fading, reject the MAI, and combat the effects of the 'near-far' problem due to imperfect power-control. It is found that the proposed receiver has excellent performance under these different scenarios.

MODEL OF THE CDMA SYSTEM

The block diagram of an asynchronous CDMA system is shown in Figure 1. The system model consists of K simultaneous users. Each user is assigned a unique signature waveform.
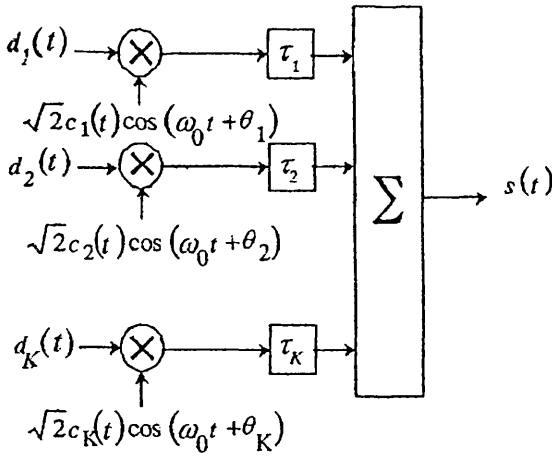
Figure 1: Asynchronous phase-coded CDMA model.

The kth user's signature sequence is $c_k(t)$ and consists of bipolar chips of duration T_c. The kth user's transmitted signal is:

$$s_k(t) = \sqrt{2}d_k(t)c_k(t)\cos(\omega_0 t + \theta_k) \qquad (1)$$

where $d_k(t)$ is a polar data bit with amplitude ± 1 and length, T_b. $T_b = NT_c$ where N is the length of the signature sequence in chips. The transmitted signal is of the form:

$$s(t) = \sum_{k=1}^{K} s_k(t - \tau_k) \qquad (2)$$

In (2), τ_k is a random delay that is assumed to be uniformly distributed over $(0, T_b)$. The received signal in an AWGN channel is of the form:

$$r(t) = \sum_{k=1}^{K} \sqrt{P_k} s_k(t - \tau_k) + n(t) \qquad (3)$$

where P_k is the received power of the kth user's signal. In a multipath channel with impulse response, $h_d(\tau;t)$, the desired user's received signal is:

$$r_d(t) = s_d(t - \tau_d) * h_d(\tau;t) + n(t) \qquad (4)$$

where:

$$h_d(\tau;t) = \sum_{i=0}^{L-1} a_i(t)e^{-j\theta_i(t)}\delta[\tau - iT_c] \qquad (5)$$

In (5), L is the number of paths, iT_c is the excess delay of the ith multipath signal relative to the line of sight delay, $a_i(t)$ is the amplitude of ith multipath signal and $\theta_i(t)$ is the phase of ith multipath signal.

THE ADAPTIVE NEURAL NETWORK RECEIVER

After converting the received signal to baseband, it is passed through a chip matched-filter and sampled at the end of every chip interval. These samples are fed into the tapped delay-line and this converts the serial received signal to parallel form. The number of taps in the delay-line is equal to the period of the signature waveform, in the usual way.

The outputs of the tapped delay-line are fed into the input layer of the multi-layer neural network. Let W_{li} be the connection weight from the ith node in the input layer to the lth node in hidden layer and φ_l is a threshold associated with the lth node in hidden layer. The output of the lth node in hidden layer is [13]:

$$O_l = f\left(\sum_{i=1}^{N} W_{li}X_i + \varphi_l\right) \qquad (6)$$

where X_i is the input signal from i^{th} input node and N is the number of input nodes. $f(.)$ is the activation function which has the form:

$$f(x) = \tanh(x) \qquad (7)$$

Let W_{jl} be the connection weight from the lth node in the hidden layer to the jth node in output layer, O_l is the output of lth hidden layer and Φ_j is a threshold associated with the jth node in output layer. The output from the jth output layer is:

$$O_j = f\left(\sum_l W_{jl}O_l + \phi_j\right) \qquad (8)$$

Weights are updated during the training mode *via* the back propagation (BP) algorithm [13], which performs the steepest descent on a surface in weight space. For example, the weight from the lth node in the hidden layer to the jth node in the output layer, W_{jl} is updated as follows:

$$W_{jl}(k+1) = Wjl(k) - \alpha \cdot \delta_{jl} \cdot O_l$$
$$\delta_{jl} = (1 - O_l^2) \cdot (T_l - O_l) \qquad (9)$$

Here, T_l is the desired output and α is the step size. On the other hand, the weight from the ith node in the input layer to the lth node in the hidden layer, W_{li} is updated with δ_{li} as follows:

$$\delta_{li} = (1 - O_l^2) \cdot \sum_j \delta_{jl}W_{jl} \qquad (10)$$

Figure 2, overleaf, shows the structure of adaptive neural network receiver.

SIMULATION AND RESULTS

To verify the ability of the adaptive neural network receiver to reject multiple access interference, an adaptive receiver with 31 nodes in the input layer, 15 nodes in the hidden layer and one node in the output layer was simulated. The weights were tuned using the back

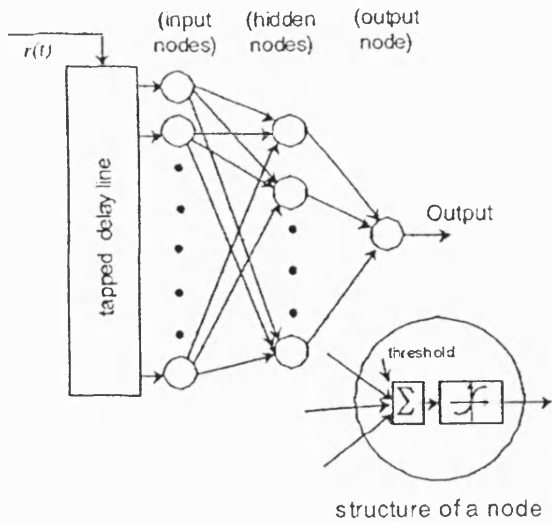propagation algorithm during the initial training mode.

Figure 2: The structure of two layers adaptive neural network receiver

The spreading sequences for all users were chosen from a set of Gold codes of length 31 and it was assumed that the receiver knew these codes during the training mode. BPSK modulation was used for all users. The relative clock offset, τ_k, of all users was chosen to be zero to simulate the synchronous mode of operation of the system. For comparison, a conventional matched filter receiver with a RAKE combiner was also simulated under identical conditions.

Figure 3 shows the sum-squared error of the adaptive neural network receiver during the training mode for a 10-user scenario for two different step sizes, α.
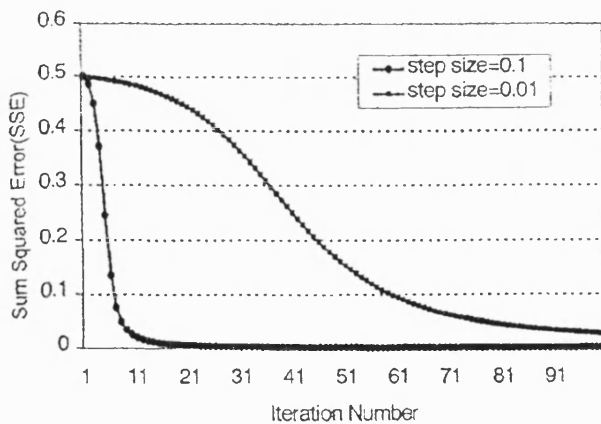
Figure 3: Sum-Squared Error (SSE) of the adaptive neural network in training mode with 10 users and 31 chips per bit.

In this situation, the system is stable and with a step size α = 0.1, the convergence performance is acceptable. The

BER of the conventional and adaptive neural network receivers in AWGN and a multi-user channel with 10 active users is shown in Figure 4.
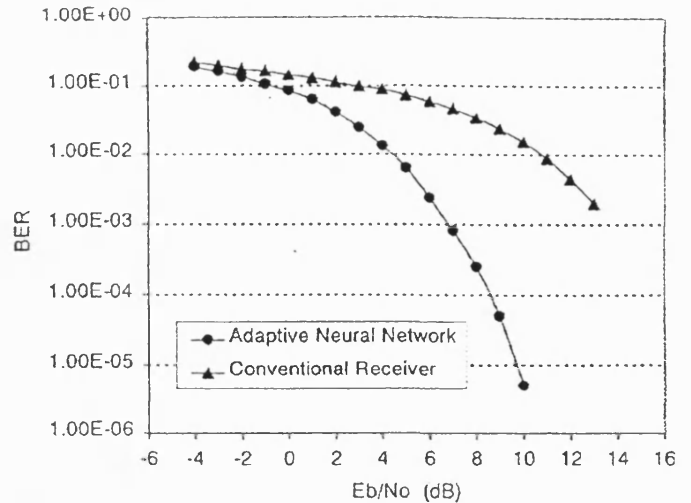
Figure 4: BER of conventional and adaptive neural network receivers in a 10-user multiple access channel and E_i/E_b(desired)=6 dB.

The energy of each interfering user is 6 dB more than the energy of desired user (representing unequal power control). It can be seen that the adaptive neural network receiver outperforms the conventional receiver in the presence of strong MAI.

Figure 5 shows the performance of the two systems under similar conditions to the previous case (i.e. multi-user interference and an AWGN channel with 10 active users).
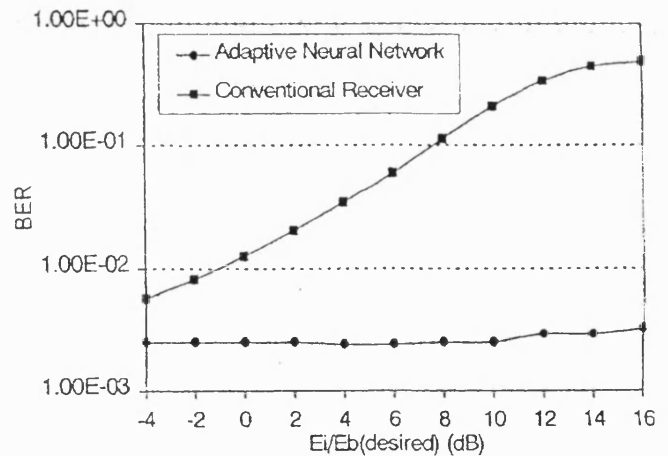
Figure 5: BER of conventional and adaptive neural network receivers in a 'Near-Far' environment for a 10-user channel and E_b(desired)/N_0=6 dB.

In addition, the effect of unequal received power for each user, simulating the 'near-far' effect is also considered. In

this situation, the ability of the adaptive neural network receiver to reject the effect of other-user interference for a wide range of energies for the interfering signals is far better than for the conventional receiver, where accurate power control is virtually mandatory.

In Figure 6, the effect of the number of users on the BER is shown for both the adaptive neural network receiver and the conventional matched-filter receiver.
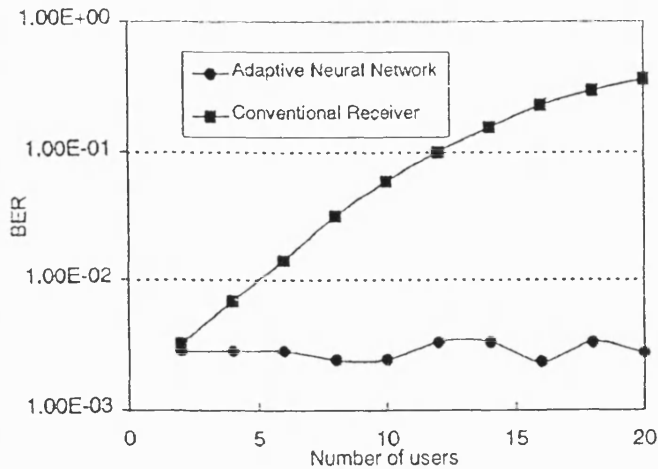
Figure 6: Bit Error Rate versus number of active user in a multiple access channel with Eb(desired)/N_0=6 dB and Ei/Eb(desired)=6dB.

The conditions are identical for both cases and represent multi-user interference and an AWGN channel with different numbers of active users and a 6dB 'near-far' situation. The adaptive neural network receiver has a much better performance in combating the effect of increasing the number of other users than the conventional matched filter receiver, which shows considerable degradation as the number of users is increased.

MULTIPATH FADING CHANNEL

The multipath channel model used in this paper is a tapped delay line of six taps, which is spaced according to the GSM channel impulse response. It is assumed that the carrier frequency is 900 MHz and the chip-rate of the spread-spectrum signal is 3.1×10^6 chips/sec and that each delay in the channel model is approximately 0.2 μsec. The output from each tap is multiplied by a coefficient, which represents the average multipath signal strength expected at that delay. The weighting factors are chosen from the urban impulse response model shown in table 1 of the COST 207 model. The outputs from all taps are then added together and normalised to provide a specific bit energy.

Figure 7 shows the sum-squared error of the adaptive neural network receiver in its training-mode with 10 users and a 6-ray multipath channel.

| Path	1	2	3	4	5	6
Delay (μsec)	0.0	0.2	0.6	1.6	2.4	5
Gain (dB)	-3	0	-2	-6	-8	-10

Table 1: Six tap specification for the urban environment.
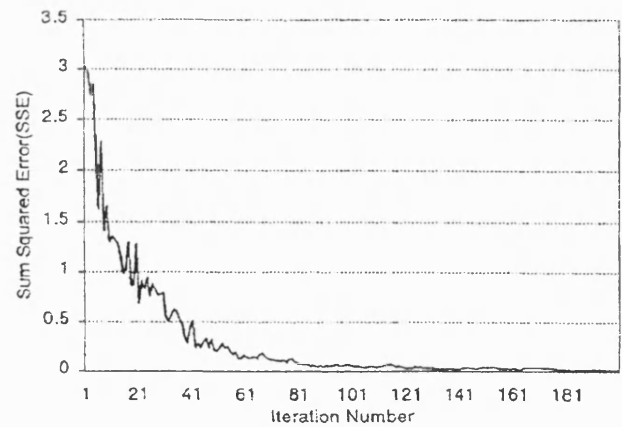
Figure 7: Sum-Squared Error (SSE) of adaptive neural network CDMA receiver in training mode for a 6-ray COST207 multipath channel and 10 users (31 chips per bit).

A back propagation training algorithm is used and the step size, α, is equal to 0.1. It is assumed that the adaptive neural network receiver knows only the signature waveform of all users and their respective time delays in the multipath channel. In this situation the system is stable and the convergence performance is good.

The BER performance of the conventional digital matched-filter receiver with RAKE combining and the adaptive neural network receiver in a 6-ray multipath channel are compared in Figure 8 for the case of AWGN and a multi-user channel with 10 active users. The energy of each interfering user is 6 dB more than the energy of desired user. In comparison with the conventional RAKE receiver, it can be seen that the adaptive neural network receiver has an excellent performance for combating the effect of multipath and rejecting the strong MAI. In fact, in this situation the adaptive neural network receiver is performing three functions. The first is a matched-filter to despread the desired user signal. The second is a RAKE receiver to collect the energy from the different paths of the desired signal in the multipath channel and the third is an interference rejection receiver for rejecting other users signals in a 'near-far' environment.
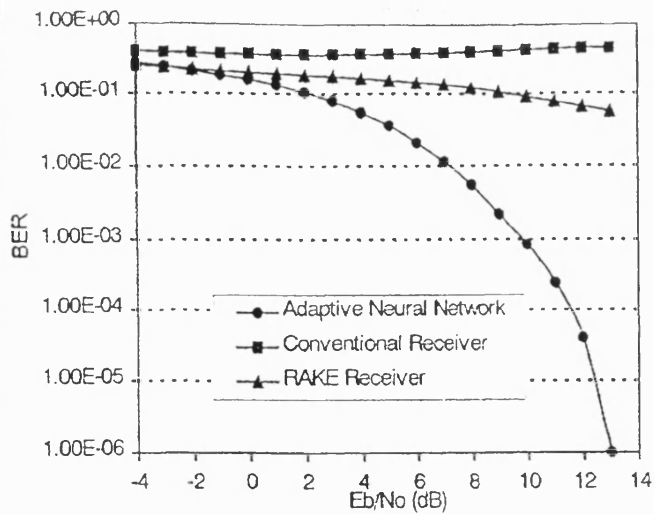
Figure 8: BER of conventional, RAKE and adaptive neural network receivers in 6-ray COST207 multipath channel with 10 user multiple access and E_i/E_b(desired)=6 dB.

CONCLUSIONS

The paper has presented a comparison of the performance of an adaptive neural network receiver with a conventional digital matched filter receiver with RAKE combining investigated through computer simulation. The key feature of the comparison is that the new system provides signal despreading, combats multipath fading and MAI as well as the effect of unequal power control resulting from the near-far effect. It is shown that this receiver, through training, learns to collect different rays and maximise the energy of the desired user and minimise the cross-correlation of other users. The learning speed of adaptive neural network receiver is very high and it has extremely good stability during the fast training mode. The BER performance of this receiver is acceptable for a variety of situations of multiple access channels and invariably outperforms the conventional digital matched filter receiver with RAKE combining.

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Neural Network Multi-User Receiver for Direct-Sequence Code-Division Multiple-Access (DS-CDMA) Multimedia Systems

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Abstract- The capacity of a direct-sequence code-division multiple-access cellular radio system is severely degraded by multiple access interference (MAI) produced by other co-channel users. A number of methods have been proposed to cancel MAI. The optimum multi-user detector has good performance when used in the base station but it has a complexity that grows exponentially with the number of users. Currently, it is too complex to implement in commercial systems. The decorrelating receiver has a computational complexity that only grows linearly with the number of users and is one of a number of sub-optimal techniques. The disadvantage of this method is the need for inverting the correlation matrix of users' signatures in real time. In this paper a new neural network receiver is presented which has a low computational complexity. It is shown that this receiver has a very good performance in combating the effect of co-channel multiple access interference and offers good cellular capacity.

Keywords- CDMA, multimedia system, cellular mobile radio, multi-user detector, neural network.

I. INTRODUCTION

Direct-sequence code-division multiple-access (DS-CDMA) is attractive for next generation wireless multiple access communications for a number of important operational reasons. It offers the prospect of universal frequency reuse, soft capacity and soft handover. Through the use of the RAKE receiver, the spread-spectrum modulation of DS-CDMA can be used to exploit the diversity in multipath signals typical of the cellular mobile radio channel. It can also provide limited interference rejection (at the expense of reduced capacity) and, in interference limited conditions, the DS-CDMA approach can provide improved capacity compared with traditional multiple access schemes such as frequency division multiple access (FDMA) and time division multiple access (TDMA).

Multiple access interference (MAI) produced by the other co-channel users is a major limitation to the capacity of a DS-CDMA system. A potential solution to this problem, particularly when used in the base station for the reverse channel, is the optimum multi-user detector. This consists of a bank of matched filters followed by a Viterbi maximum likelihood (ML) detector [1] to cancel out the effect of MAI. The computational complexity of this detector increases exponentially with the number of users however and it is currently too complex to implement in commercial systems.

The decorrelating receiver is one of a number of sub-optimal detectors proposed recently to reduce the effect of MAI. This receiver has a computational complexity which only grows linearly with the number of users [2,3]. The major disadvantage of this particular receiver, however, is the need for inverting the correlation matrix of users' signatures in real time.

A particularly interesting method of multi-user detection, which has the potential for low computational complexity, is the application of neural network concepts. The first paper that considered the application of neural network receivers to multi-user detection is due to Aazhang, Paris and Orsak [4]. They proposed a detection system that uses a multilayer neural network. Miyajima [5] proposed a Hopfield neural network for multi-user detection that uses the likelihood function as the energy function to be minimised.

In this paper, a new neural network receiver with low complexity for DS-CDMA systems is investigated and a comparative performance analysis with the decorrelating receiver is carried out via a Monte Carlo simulation.

It is observed that the proposed receiver is able to combat the effect of MAI and has acceptable performance in different scenarios.

The remainder of this paper is organised as follows. In the following section, the system and channel models are described. In section III, the neural network receiver's structure is considered and in section IV, results obtained from a simulation of the system are presented. Section V provides some conclusions of the study.

II. MODEL OF A SYNCHROUNOUS CDMA SYSTEM

The system model consists of K simultaneous users, whereby each user is assigned a unique signature waveform. The kth user's signature sequence is $c_k(t)$ and consists of bipolar rectangular pulses with a sequence period NT_c, where $N = T_b / T_c$. T_b and T_c are the bit and chip periods, respectively. The kth user's transmitted signal is:

$$s_k(t) = \sqrt{2} A_k d_k c_k(t) \cos(\omega_0 t + \theta_k) \qquad (1)$$

where A_k is the amplitude of the carrier signal and d_k is a polar data bit with amplitude ± 1 and duration T_b. The channel is assumed to be

represented by an AWGN channel shared by all the co-channel users. Consequently, the received signal is given by:

$$r(t) = \sum_{k=1}^{K} A_k c_k(t) d_k + n(t) \qquad (2)$$

The simplest CDMA receiver is the conventional matched filter that uses a bank of matched filters for extracting data. The matched filter output is given by:

$$h_{i,k} = \frac{1}{T_b} \int_0^{T_b} c_i(t) c_k(t) dt \qquad (3)$$

Here, if $i = k$, $h_{i,k} = 1$ and if $i \neq k$, $0 \leq h_{i,k} \leq 1$. The output of the kth user's correlator for a particular bit interval is:

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

$$= A_k d_k + \sum_{\substack{i=1 \\ i \neq k}}^{N} h_{i,k} A_i d_i + \frac{1}{T_b} \int_0^{T_b} n(t) c_k(t) dt \qquad (4)$$

$$= A_k d_k + MAI_k + z_k$$

In other words, correlation of the received signal with the kth user itself gives rise to the recovered data term $(A_k d_k)$, correlation with the other users gives rise to multiple access interference (MAI_k) and correlation with the thermal noise gives rise to the noise term z_k. It dose not take into account other co-channel users and implements a single user detector strategy. It is straightforward to predict that this type of receiver does not have a very good performance in multi-user channels.

The optimum receiver is defined as the receiver that selects the vector of most probable data bits for each user $\{d_k(n), 1 \leq k \leq K\}$ given the received signal $r(t)$ observed over the interval $0 \leq t \leq T_b$. It consists of a bank of K correlators or matched filters followed by a detector that computes the 2^K correlation metrics and selects the vector of user data bits corresponding to the largest correlation metric. To achieve this, however, the receiver must have several pieces of knowledge, a priori. It should have knowledge of the all the received signal amplitudes of each user's transmission and from this it computes the correlation metrics for all 2^K possible choices of the bits in the information vector and selects the sequence that gives the largest correlation metric.

This approach is too complex to be implemented in practice because K is generally large.

The decorrelating receiver is a sub-optimal detector that has a linear computational complexity and can significantly reduce the effect of MAI [2,3]. Equation (4) can be written for all K users as:

$$y_1 = \sum_{i=1}^{K} h_{i,k} A_i d_i + z_1 , \quad y_2 = \sum_{i=1}^{K} h_{i,k} A_i d_i + z_2 , \cdots$$

$$y_K = \sum_{i=1}^{K} h_{i,k} A_i d_i + z_K \tag{5}$$

or in matrix form:

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ \vdots \\ y_K \end{bmatrix} = \begin{bmatrix} 1 & h_{2,1} & \cdots & \cdots & h_{K,1} \\ h_{1,2} & 1 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ \vdots & & \ddots & \ddots & \vdots \\ h_{K,1} & \cdots & \cdots & \cdots & 1 \end{bmatrix} \begin{bmatrix} A_1 & 0 & \cdots & \cdots & 0 \\ 0 & A_2 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ \vdots & & \ddots & \ddots & 0 \\ 0 & \cdots & \cdots & 0 & A_K \end{bmatrix} \begin{bmatrix} d_1 \\ d_2 \\ \vdots \\ \vdots \\ d_K \end{bmatrix} + \begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ \vdots \\ z_K \end{bmatrix} \tag{6}$$

or, equivalently as:

$$Y = H.A.d + Z \tag{7}$$

d is the data vector, Z is a noise vector and Y is the matched filter output vector. A is a diagonal matrix containing the *a priori* received amplitudes and H is a $K \times K$ correlation matrix that contains the values of correlations between every pair of codes. Since $h_{i,k} = h_{k,i}$, H is symmetric and invertible for synchronous systems [3]. The decorrelating detector applies the inverse of H to the conventional detector outputs. The estimate of the data is:

$$\hat{d}_{dec} = Sgn(H^{-1}Y) = Sgn(A.d + H^{-1}Z) =$$
$$Sgn(A.d + Z_{dec}) \tag{8}$$

As can be seen, the decorrelating receiver eliminates the MAI. However, it is clear that it needs the inverse of the correlation matrix of users' signatures and the major disadvantage of this receiver is doing this in real time.
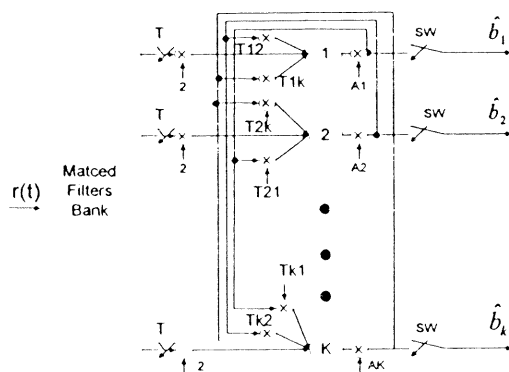

Figure1 Block diagram of the recurrent neural network receiver.

III. NEURAL NETWORK MULTI-USER DETECTOR

Figure 1 shows the structure of the recurrent neural network multi-user receiver.

After converting the received signal to baseband, it passes through a chip matched filter and is sampled at the end of every chip interval. These samples are fed into a bank of matched filters. The number of matched filters in the filter bank is equal to the number of users, K. The outputs of the matched filters are sampled every bit interval and are fed into the input of the recurrent neural network.

The recurrent neural network has a structure that consists of a number of small non-linear processing units. Each unit contains a summer and a non-linear function. The output of each unit is fed to all other units via connection weights and each unit has an external input. Hopfield [6] showed that when the connection weights are symmetric the dynamic of the recurrent neural network always lead to a stable state that the energy function E, is minimum.

$$E = -\sum_{k=1}^{N} V_k I_k - \frac{1}{2} \sum_{k=1}^{N} \sum_{j=1}^{N} T_{kj} V_k V_j \tag{9}$$

In equation 9, E is energy, V_k is the output of kth unit, I_k is the external input to k^{th} unit, T_{kj} is the connection weight from j^{th} to k^{th} unit and N is the number of units.

By using $I_k = 2Y_k$, $V_k = A_k b_k$, $N = K$, and $T_{kj} = -2h_{kj}$, the recurrent neural network structure can be used as a multi-user detector in the multiple access environment.

IV. SIMULATION AND RESULTS

To verify the ability of neural network receiver in multi-user environment and combating the effect of co-channel other user interference; recurrent neural network. conventional match filter and decorrelating receivers have been simulated. The spreading sequences for all users were chosen (arbitrarily) to be of length 31. Also BPSK modulation was used for all users. Recurrent neural network receiver uses the cross-correlation of user's signature as parameters in its structure.

The recurrent neural network receiver uses the outputs of the bank of matched filters as external inputs to the neural network and it also uses the cross-correlation of a user's signature and the amplitude of the received signals as parameters in its structure. The receiver's parameters were as $I_k=2Y_k$, $V_k=A_kb_k$, $N=K$, and $T_{kj}=-2h_{kj}$. The self-connection factor T_{kk} was selected zero. Under this assumption the system will always have a global minimum [7].

The BER performance of the conventional matched filter receiver, the decorrelating receiver and the neural network receiver are shown in figure 2 for an AWGN channel and co-channel interference from 6 active users.
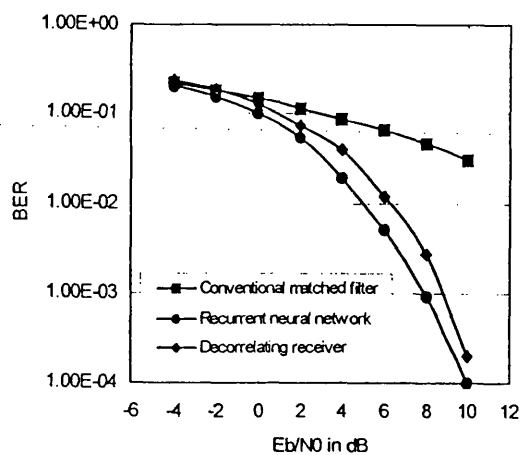

Figure 2 BER of recurrent neural network, decorrelating and conventional matched filter receivers in AWGN and 6-user CDMA channel.

In this case the received energy per bit is the same for each user. It can be seen that the recurrent neural network receiver outperforms the conventional receiver and the decorrelating receiver in rejecting multiple access interference.

Figure 3 shows the ability of the three receivers in handling imperfect power control of the various users due to the 'near-far' effect in the CDMA environment. In this case, the $E_b(desired)/N_0$ of the wanted signal is set at 6dB whereas all the unwanted users have an equal energy per bit, E_i. As can be seen, the performance of the recurrent neural network is substantially better than both the conventional matched filter and the decorrelating receiver. The lower complexity of recurrent neural network receiver makes it attractive for implementing in multiple access environments.
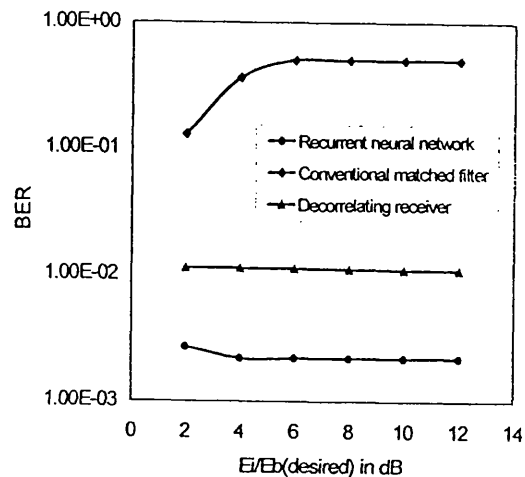
Figure 3 BER of recurrent neural network, conventional matched filter and decorrelating receivers in 6-user 'Near-Far' environment ($E_{b(desired)}/N_0=6$ dB).

V. CONCLUSION

The performance of a recurrent neural network receiver for rejecting the effect of MAI in a 'Near-Far' multiple access CDMA channel has been investigated using a Monte-Carlo simulation. It has been shown that this receiver is extremely suitable for combating the effect of co-channel interference and is better than both the conventional matched filter and the decorrelating receivers. In addition the recurrent neural network as a ver low implementation complexity. The good performance and low implementation complexity of recurrent neural network receiver makes it attractive for the next generation of wireless multimedia systems.

Low Complexity Neural Network Structure for Implementing the Optimum Maximum-likelihood Multi-User Receiver in a DS-CDMA Communication System

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Abstract: The capacity of direct-sequence code division multiple access systems is interference limited, particularly by multiple-access interference produced by other co-channel users. The optimum multi-user receiver calculates the maximum-likelihood ratio of the detected data for all users simultaneously, but it has a complexity that grows exponentially with the number of users. In this paper, a neural network approach to multi-user detection is considered. It is shown that the performance of this receiver is the same as the maximum-likelihood multi-user receiver but it has a much lower computational complexity.

I. INTRODUCTION

Direct-sequence code-division multiple access systems (DS-CDMA) are attractive for wireless multiple-access communications because they offer universal frequency re-use, good performance in interference limited conditions and provide a flexible approach to variable rate data. However, multiple-access interference (MAI) produced by the other co-channel users is a significant limitation to the capacity of conventional DS-CDMA systems.

A potential solution to this problem is the maximum-likelihood multi-user detector [1]. This comprises a bank of matched filters followed by a maximum-likelihood detector. Each filter in the bank is matched to a particular user's signature waveform and its output is sampled at the data rate. The maximum-likelihood estimates of the transmitted data sequences are obtained by processing the output of the matched filters with a Viterbi algorithm [1]. However, the computational complexity of this detector increases exponentially with the number of users and it is currently too complex to implement in commercial systems.

An interesting approach to multi-user detection in DS-CDMA communications draws on the concept of the neural network. In this paper, we examine the use of the neural network from the point of view of offering low computational complexity. This is possible because neural networks use simple non-linear processing units in a powerful parallel structure to implement signal-processing functions.

The first paper that considered the application of neural network receivers to multi-user detection is due to Aazhang *et al* [2]. They proposed a detection system that used a multi-layer neural network. They assumed that the signature waveforms were known *a priori* and training sequences were used to 'train' the neural network to respond appropriately to the network inputs from the matched filter outputs. In [3], a radial basis function neural network was proposed for single-user detection and this type of neural network was extended to synchronous multi-user detection in [4]. Miyajima *et al* [5] proposed a recurrent neural network for synchronous multi-users detection using the likelihood function as the energy function to be minimised. In their approach, the weights of the network were non-adaptive and pre-set to be equal to the cross-correlation of the signature waveforms.

In this paper, a low complexity neural network receiver for DS-CDMA systems is investigated and a comparative performance analysis is carried out *via* Monte Carlo simulation. It is found that if additional information concerning the amplitude of the receiver signals is incorporated into the neural network parameters, the proposed receiver has a performance that is virtually indistinguishable from the optimum maximum-likelihood multi-user receiver when operated in several different multi-user scenarios.

In the next section, the system and channel models are described. The maximum-likelihood and the recurrent neural network receivers are considered in sections III and IV. Section V, presents results obtained from a system simulation and Section VI provides some conclusions of the study.

II. MODEL OF A DS-CDMA SYSTEM

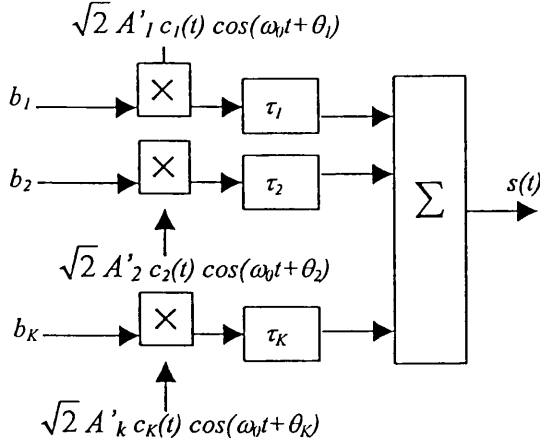The block diagram of an asynchronous CDMA system is shown in Figure 1.

Figure 1: Asynchronous phase-coded CDMA model.

The system model consists of K simultaneous users. Each user is assigned a unique signature waveform. The kth user's signature is $c_k(t)$ and consists of bipolar chips of duration T_c. The kth user's transmitted signal is:

$$s_k(t) = \sum_{i=1}^{L} \sqrt{2} A_k'(i) b_k(i) c_k(t - iT_b) \cos\left(\omega_0(t - iT_b) + \theta_k\right)$$

(1)

where A_k' is the amplitude of the kth transmitted signal, b_k is a polar data bit with amplitude ± 1 and length, $T_b = NT_c$, where N is the length of the signature sequence in chips. L is the number of data bits in a data block.

The transmitted signal has the form:

$$s(t) = \sum_{k=1}^{K} s_k(t - \tau_k)$$

(2)

In equation (2), τ_k is a random delay that is assumed uniformly distributed over $(0, T_b)$.

The demodulated received signal in an AWGN channel is of the form:

$$r(t) = \sum_{k=1}^{K} \sum_{i=1}^{L} A_k(i) b_k(i) c_k(t - iT_b - \tau_k) + n(t)$$

(3)

where $A_k(i)$ is the received amplitude of the kth user's signal for the ith data bit and $n(t)$ is additive white Gaussian noise (AWGN), with power spectral density, $N_0/2$.

III. THE MAXIMUM-LIKELIHOOD MULTI-USER RECEIVER

The maximum-likelihood receiver is defined as the receiver that selects the most probable sequence of

bits, $b_k(n)$, for $1 \le k \le K$ and $1 \le n \le L$, given the received signal $r(t)$ observed over the interval $0 \le t \le LT_b + 2T_b$ [6]. For synchronous data transmission and in AWGN, it is sufficient to consider the received signal in the time interval $0 \le t \le T_b$. Over this interval the received signal is:

$$r(t) = \sum_{k=1}^{K} A_k b_k c_k(t) + n(t)$$

(4)

In this case, the maximum-likelihood receiver is defined as the receiver that selects the vector of the most probable data bits for each user $\{b_k, 1 \le k \le K\}$ given the received signal $r(t)$ observed over the time interval $0 \le t \le T_b$ [1]. The optimum maximum-likelihood (ML) receiver computes the log-likelihood function Λ (b) and selects the data bits $\{b_k, 1 \le k \le K\}$ that minimise Λ (b) or maximises the correlation metrics, $C(Y_K, b_K)$, defined as:

$$\Lambda \ (b) = \int_0^{T_b} \left[r(t) - \sum_{k=1}^{K} A_k b_k c_k(t) \right]^2 dt$$

(5)

$$C(Y_K, b_K) = 2 \sum_{k=1}^{K} A_k b_k y_k - \sum_{i=1}^{K} \sum_{k=1}^{K} A_k A_j b_k b_j h_{j,k}$$

(6)

where:

$$y_k = \int_0^{T_b} r(t) c_k(t) dt, \text{ for } 1 \le k \le K$$

represents the correlation of the received signal $r(t)$ with the kth user's signature code and

$$h_{jk} = \int_0^{T_b} c_j(t) c_k(t) dt, \text{ for } 1 \le j, k \le K$$

is the correlation between code $c_j(t)$ and $c_k(t)$.

The maximum-likelihood detector has to compute the correlation metrics for all 2^K possible choices of the bits in the information sequence of K users and from this select the sequence that gives the largest correlation metrics.

For an asynchronous DS-CDMA system, 2^{LK} correlation metrics must be computed to determine the K blocks of sequences, each of which has a length, L. This approach is too complex to be implemented in practice because K and L are generally large.

IV. THE RECURRENT NEURAL NETWORK MULTI-USER RECEIVER

The recurrent neural network, shown in Figure 2, has a structure that consists of a number of small non-linear processing units or neurons. Each neuron contains a summer and a non-linear function. The output of each neuron is fed to all other neurons via connection weights. The feedback configuration enables the network to store information in a

dynamically stable configuration. Input signals (i.e. the outputs from the bank of matched filters) can be entered as inputs to the neurons directly, as shown in Figure 2, and in this situation the network is able to map input patterns to the desired outputs.

The dynamical behaviour of a recurrent neural network that includes N neurons is uniquely described by a parameter set $\{W, I\}$. $W=\{w_{ij}\}$ is an $N \times N$ matrix whose element w_{ij} is the connection weights between j^{th} and i^{th} neurons. $I=\{I_i\}$ is a vector whose element I_i is the external input to the ith neuron. An energy function, which is bounded from below and is non-increasing when the state of network changes [7], can be defined as below:

$$E(t) = -\frac{1}{2} X^T(t) \ W X(t) - I^T X(t) \tag{7}$$

In equation (7), $X(t) = \{x_i\}$ is a vector, whose element x_i is the output of the ith neuron in the network. Hopfield [8] showed that when the non-linear functions in each neuron are bounded, monotonically increasing, and continuous, and the connection weights are symmetric, the dynamic behaviour of the recurrent neural network always leads to a stable state such that the energy function, E, is minimum. Consequently, if the network is started in any initial state, it will move in a downhill direction of the energy function until it reaches a minimum.

The recurrent neural network can be applied to the solution of a wide range of optimisation problems in signal processing by mapping the function to be optimised to the energy function of the neural network, which is then minimised.

Making the assumption of symmetrical connection weights and using the ability of the recurrent neural network to solve the optimisation problem for multi-user detection, the energy function described by equation (7) can be written as:

$$E(t) = -\frac{1}{2} \underbrace{\sum_i^K \sum_j^K w_{ij} x_i(t) x_j(t)}_{i \neq j} - \sum_{j=1}^N x_j(t) I_j \tag{8}$$

In equation (8), also it is assumed that the self-connection weights, w_{ii}, are zero. Under this assumption, the state of the network always converges to a corner of a hyper-cube where x_i has the values ±1 [5]. The convergence time of the network is very fast but for DS-CDMA applications, this increases with the number of users.

In order to apply the recurrent neural network to the problem of a multi-user detector for a DS-CDMA receiver it is necessary to convert the problem from a maximisation problem to a minimisation problem. The key to doing this lies in defining a new correlation metric, $\hat{C}(Y_K, b_K)$ in such a way that maximisation of $C(Y_K, b_K)$ minimises $\hat{C}(Y_K, b_K)$. It can be shown that:

$$\hat{C}(Y_K, b_K) = -C(Y_K, b_K) \tag{9}$$

By comparing equation (9) with equation (8), it can be seen that the maximum-likelihood multi-user detector can be implemented by a recurrent neural network structure if $I_i = 2Y_i$, $x_i = A_i b_i$, $N=K$, and $w_{ij} = -2h_{ij}$. Thus if the amplitude of the users' signals are known, or can be estimated, this information can be passed to the neural network which can then implement the ideal maximum likelihood detector.

System Complexity
The maximum-likelihood receiver computes the correlation metrics $C(Y_K, b_K)$ in equation (6) for different combinations of users' transmitted bits and chooses $b_k(n)$, for $1 \leq k \leq K$ that maximises the correlation metrics. It is clear that in this situation the complexity grows exponentially when the number of users increases. The number of additions and multiplications after the bank of matched filters that is needed to compute the correlation metrics for implementing the maximum-likelihood receiver are $2^K(K+2^K)$ additions and 2^K $[4(K/2+2^K)]$ multiplications, where K is the number of users.

If the coefficients of the recurrent neural network receiver are chosen to be $I_i = 2Y_i$, $x_i = A_i b_i$, $N=K$, and $w_{ij} = -2h_{ij}$, as described in the previous section, and the self-connection weights w_{ii} are set to zero to ensure convergence, a similar estimate of algorithm complexity can be carried out for the recurrent neural network. Assume that at the beginning of each detection period the initial values of the outputs of each neuron in the network are chosen to be zero. This determines the initial state. In this situation, the output values of the neurons are at the origin of state space and the speed of convergence time is high. The dynamic of the recurrent network converges to its steady state at most after K iterations. Hence the number of additions and multiplications that are required after the bank of matched filters to implement the recurrent neural network receiver is K^2 additions and K^3 multiplications. It is clear that the complexity of the recurrent neural network grows more slowly than the maximum-likelihood receiver when the number

of users is increased. This will have a significant impact when the multi-user receiver is implemented in hardware.

V. SIMULATION AND RESULTS

Figure 2 shows the structure of the recurrent neural network multi-user receiver used at the base-station of a DS-CDMA system. After converting the received signal to base-band, it passes through a chip-matched filter and is sampled at the end of every chip interval. These samples are fed into a bank of matched filters. The number of matched filters in the bank is equal to the number of users. The outputs of the matched filters are sampled at every bit interval and fed into the input of the recurrent neural network. The estimated data bit for the ith user is denoted, $\hat{b}_i$.
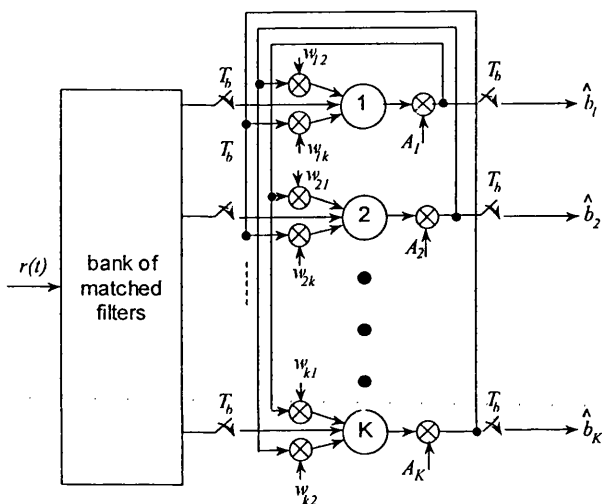

Figure 2: The structure of recurrent neural network receiver in a DS-CDMA system.

To compare the performance of the recurrent neural network multi-user receiver with the maximum-likelihood multi-user receiver under the same conditions of multi-user interference, both types of receiver were modelled by Monte-Carlo simulation.

The performance metric used is the bit error rate (BER). The spreading sequences for all users were chosen to be of length 31 and BPSK modulation was used for all users. Where appropriate, the impact of imperfect power control on the performance of the two systems was also compared. For this type of scenario, the other users are all assumed to transmit at powers above that of the desired user.

Because the performance of the two receivers are so close, the results are tabulated rather than plotted in graphical form to highlight any small differences

in performance. In the tables, $E_{b(desired)}$ represents the energy per bit of the desired user and E_i represents the energy per bit of each of the other interfering users. It is assumed that each interfering user transmits at the same power level.

E_b/N_0 in dB	Maximum-likelihood Receiver	Recurrent Neural Network
-4	0.18640	0.18696
-2	0.13002	0.13028
0	0.07715	0.07723
2	0.03664	0.03669
4	0.01178	0.01179
6	0.00231	0.00231
8	0.00006	0.00006

Table 1: BER of maximum-likelihood and recurrent neural network receivers in 6-users 'Near-Far' environment ($E_i/E_{b(desired)}$=6 dB).

Table 1 shows the BER of the two receivers as a function of $E_{b(desired)}/N_0$ in AWGN for the situation where 6-users share the CDMA channel. In this case the 'near-far' effect is simulated by allowing each of other-users to transmit at a power that is 6 dB higher than the wanted signal power (i.e. $E_i/E_{b(desired)}$ =6 dB). It can be seen the performance of the recurrent neural network receiver is the same as the maximum-likelihood receiver.

E_i/E_b in dB	Maximum-likelihood Receiver	Recurrent Neural Network
2	0.00231	0.00227
4	0.00231	0.00233
6	0.00231	0.00231
8	0.00231	0.00231
10	0.00231	0.00231
12	0.00231	0.00231
14	0.00231	0.00231

Table 2: BER of maximum-likelihood and recurrent neural network receivers in 6-users 'Near-Far' environment (E_b/N_0=6 dB).

Table 2 shows the impact of the 'near-far' effect on the BER of the wanted user by increasing the ratio $E_i/E_{b(desired)}$. In this table, 6-users are assumed to share the channel and $E_{b(desired)}/N_0$=6 dB is set for the desired user. The result shows again that the performance of the recurrent neural network receiver is identical to the maximum-likelihood receiver in a 'Near-Far' environment.

No. of Users	Maximum-likelihood Receiver	Recurrent Neural Network
2	0.00231	0.00231
4	0.00231	0.00231
6	0.00231	0.00231
8	0.00231	0.00231
10	0.00231	0.00231

Table 3: BER of maximum-likelihood and recurrent neural network receivers in 'Near-Far' environment ($E_{b(desired)}/N_0=6$ dB, $E_I/E_{b(desired)}=6$ dB).

Table 3 shows the BER performance of the two types of receiver in a 'near-far' CDMA environment as a function of the number of users. In this scenario, $E_I/E_{b(desired)}$ = 6dB for each 'other-user' and $E_{b(desired)}/N_o$ = 6dB. In this situation the performance of the recurrent neural network receiver is the same as the maximum-likelihood receiver.

The implementation complexity of the two receivers as the number of users is varied is shown in Table 4. It is clear that as the number of users is increased, the difference in implementation complexity of the maximum-likelihood and recurrent neural network receivers becomes large. For example in the 6-user scenario, the maximum-likelihood receiver needs 4480 additions and 17152 multiplications, but the recurrent neural network needs only 36 additions and 216 multiplications.

No. of Users	Maximum-likelihood Receiver	Recurrent Neural Network
2	24X+80Y	4X+8Y
4	320X+1152Y	16X+64Y
6	4480X+17152Y	36X+216Y
8	67584X+266240Y	64X+512Y

Table 4: Complexity of maximum-likelihood and recurrent neural network receivers in multi-user CDMA environment

(X= number of add, Y= number of multiply).

VI. CONCLUSIONS

The performance of a recurrent neural network receiver for rejecting the effect of MAI in a 'Near-Far' multiple-access CDMA channel has been investigated using a Monte-Carlo simulation. It has

been shown that this type of receiver is extremely suitable for combating the effect of co-channel multiple access interference and its performance is the same as the maximum-likelihood receiver. In addition, the implementation complexity of the recurrent neural network receiver, especially for the case of a large number of users, is considerably lower than the maximum-likelihood receiver. The good performance and low implementation complexity of the recurrent neural network receiver makes it attractive for implementation in the next generation of wireless mobile systems.

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