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CHANNEL AND DELAY ESTIMATION ALGORITHMS FOR WIRELESS COMMUNICATION SYSTEMS

Marius Sirbu

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Helsinki University of Technology
Department of Electrical and Communications Engineering
Signal Processing Laboratory

Teknillinen korkeakoulu
Sähkö- ja tietoliikennetekniikan osasto
Signaalinkäsittelytekniikan laboratorio

Distribution:
Helsinki University of Technology
Signal Processing Laboratory
P.O. Box 3000
FIN-02015 HUT
Tel.: +358-9-451-2486
Fax: +358-9-452-3614
E-mail:mirja.lemetyinen@hut.fi

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Abstract

This thesis addresses the problem of channel and propagation delay estimation in wireless communication systems. Channel estimation and equalization compensate for channel distortions. Consequently, transmitted data may be reliably recovered. A feasible communication link, in both single user and multi-user communications, requires synchronization between the transmitter and the receiver. Traditional channel estimation and synchronization methods use training data, therefore decreasing the effective data rates. More efficient methods which use smaller amounts of training data are of great interest. In particular blind equalization methods, as well as receiver based synchronization methods enable higher effective data rates.

In Global System for Mobile Communications (GSM) more than 22% of the transmitted signal is used for channel estimation and synchronization purposes. If blind equalization methods could be applied in GSM, this part of the signal could be used for transmitting information bits. Blind channel identifiability problems in GSM are investigated in this thesis. The performance of several blind equalization methods is also evaluated, for both the Gaussian Minimum Shift Keying (GMSK) modulation and for the 8-Phase Shift Keying (8-PSK) modulation proposed for the future evolution of the GSM, Enhance Data Rates for Global Evolution (EDGE). Blind equalization methods are feasible for GSM in low mobility scenarios.

The uplink (mobile to base station (BS) link) in direct-sequence code division multiple access (DS-CDMA) wireless networks is asynchronous. A DS-CDMA receiver has to simultaneously estimate channel impulse responses (CIR) and propagation delays for the active users. Commercial CDMA based systems use long spreading codes, with the period much longer than the symbol period. In this thesis, a novel uplink multi-user adaptive receiver is developed for long-code DS-CDMA. It is also capable of tracking time variations of the channels. Multiple antennas are considered at the receiver end, taking advantage of the signal to noise ratio (SNR) gain and the antenna diversity gain. A specific system model is developed, characterized by a channel matrix which also includes the effect of the propagation delays. Estimating the channel matrix leads to the implicit estimation of the propagation delays. Algorithms for the explicit estimation of the propagation delays are also derived. The proposed receiver structures are capable of estimating and tracking the impulse responses of the channels and synchronizing the active users by using low complexity adaptive techniques.

This thesis also addresses the problem of channel estimation and time synchronization in Orthogonal Frequency Division Multiplex (OFDM) systems. OFDM is robust with regard to frequency selective channels but is very sensitive to time and frequency synchronization errors. A novel low-complexity iterative method is developed for channel and time-offset estimation in OFDM by using a system model specific to fixed wireless links, e.g. wireless local area networks (WLAN) IEEE 802.11 standard.

Preface

The research work for this thesis was carried out at the Signal Processing Laboratory, Helsinki University of Technology during the years 2000-2003. The research group is member of SMARAD, Center of Excellence of the Academy of Finland.

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List of original publications

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M. Sirbu, J. Mannerkoski, Y. Zhang and V.Koivunen. Feasibility of fractionally spaced blind equalization with GMSK modulated signals, In *Proceedings of European Conference on Circuit Theory and Design (ECCTD'01)*, vol. I, pp. 45-48, Espoo, Finland, August 2001.

II

M.Sirbu, J. Mannerkoski, Y. Zhang and V. Koivunen. On the feasibility of blind equalization for EDGE systems, In *Proceedings of IEEE Workshop on Signal Processing Advances on Wireless Communications (SPAWC'01)*, pp. 90-93, Taoyuan, Taiwan, March 2001.

III

M. Sirbu and V. Koivunen. Channel estimation and tracking in uplink asynchronous DS/CDMA using multiple antennas, In *Proceedings of International Conf. On Digital Signal Proc. (DSP'02)*, pp. 635-638, Santorini, Greece, July 2002.

IV

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V

M. Sirbu and V. Koivunen. Propagation delay estimation in asynchronous DS/CDMA using multiple antennas, In *Proceedings of European Signal Processing Conference, (EUSIPCO'02)* , pp. 653-656, Toulouse, France, September 2002.

VI

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VII

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VIII

M. Sirbu and V. Koivunen. Delay estimation in long-code synchronous DS/CDMA systems using multiple antennas, Helsinki University of Technology, Signal Processing Laboratory, Technical Report 42, ISBN 951-22-6699-7, Submitted for publication to *Eurasip Journal on Wireless Communications and Networking*, October 2003.

IX

M. Sirbu and V. Koivunen. One-step refinement method for joint channel estimation and timing acquisition in OFDM transmission , In *Proceedings of the IEE&IEEE International Workshop on Signal Processing for Wireless Communications (SPWC'03)*, pp. 261-264, London, UK, May 2003.

List of abbreviations and symbols

Abbreviations

AR	Auto-Regressive
ADSL	Asymmetric Digital Subscriber Line
AoA	Angle of Arrival
AML	Approximate Maximum Likelihood
AWGN	Additive White Gaussian Noise
BER	Bit Error Rate
BPSK	Binary Phase Shift Keying
BS	Base Station
BU	Bad Urban
C/A	Coarse/Acquisition
CDMA	Code Division Multiple Access
CFR	Channel Frequency Response
CIR	Channel Impulse Response
CLMF	Chip-delay Locked Matched Filter
CMA	Constant Modulus Algorithm
CMF	Chip Matched Filter
CMOE	Constraint Minimum Output Energy
CP	Cyclic Prefix
CRLB	Cramer-Rao Lower Bound
CS	Cyclostationary
DAB	Digital Audio Broadcasting
DD	Decision Directed
DEMA	DEcoupled Multiuser code timing Acquisition
DFE	Decision Feedback Equalizer
DFT	Discrete Fourier Transform
DLL	Delay Locked Loop
DS-CDMA	Direct Sequence Code Division Multiple Access
DVB-T	Digital Video Broadcasting -Terrestrial
EDGE	Enhanced Data rates for Global Evolution
EKF	Extended Kalman Filter
ESPRIT	Estimation of Signals Parameters via Rotation and Invariant Technique
EVI	EigenVectror approach for blind channel Identification
FDMA	Frequency Division Multiple Access
FFT	Fast Fourier Transform
FH-CDMA	Frequency Hopping Code Division Multiple Access
FIR	Finite Impulse Response
FS	Fractionally Spaced
GCD	Generalized Correlation Decomposition
GMSK	Gaussian Minimum Shift Keying
GPRS	General Packet Radio Service
GPS	Global Positioning System
GSM	Global System for Mobile communications
HOS	Higher Order Statistics
HT	Hilly Terrain

IBI	Inter-Block-Interference
ICI	Inter-Carrier-Interference
IC	Interference Cancellation
IDFT	Inverse Discrete Fourier Transform
i.i.d.	independent and identically distributed
IIR	Infinite Impulse Response
ISI	Inter-Symbol-Interference
LMS	Least Mean Squares
LMMSE	Linear Minimum Mean Square Error
LOS	Line Of Site
LS	Least Squares
LSML	Large Sample Maximum Likelihood
MC-CDMA	Multi-Carrier Code Division Multiple Access
MIMO	Multiple-Input-Multiple-Output
MISO	Multiple-Input-Single-Output
ML	Maximum Likelihood
MLSE	Maximum Likelihood Sequence Estimator
MOE	Minimum Output Energy
MMSE	Minimum Mean Square Error
MSE	Mean Square Error
MUD	Multi-User Detector
MUI	Multiple User Interference
MUSIC	MUltiple SIgnal Classification
MVDR	Minimum Variance Distortionless Response
NFR	Near-Far Ratio
OFDM	Orthogonal Frequency Division Multiplexing
PCS	Personal Communication System
PIC	Parallel Interference Cancellation
PSK	Phase Shift Keying
QAM	Quadrature Amplitude Modulation
QPSK	Quadrature Phase Shift Keying
RA	Rural Areas
RLS	Recursive Least Squares
SER	Symbol Error Rate
SIC	Successive Interference Cancellation
SIMO	Single Input Multiple Output
SIR	Signal to Interference Ration
SNR	Signal to Noise Ratio
SOCS	Second-Order Cyclostationary Statistics
TDMA	Time Division Multiple Access
TU	Typical Urban
UMTS	Universal Mobile Telecommunication System
VCO	Voltage Controlled Oscillator
WLAN	Wireless Local Area Network
WS	W-Slice
WSCS	Wide-Sense CycloStationary
WSS	Wide-Sense Stationary
WSSUS	Wide-Sense Stationary Uncorrelated Scattering
ZP	Zero Padding
ZF	Zero Forcing

Symbols

a	scalar
a^*	complex conjugate of the scalar a
$\Re\{a\}$	real part of a complex scalar a
$\Im\{a\}$	imaginary part of a complex number
$\hat{a}$	estimated parameter a
$\mathbf{a}$	vector
$\mathbf{a}^*$	complex conjugate of the vector $\mathbf{a}$
$\mathbf{a}^T$	transposed of the vector $\mathbf{a}$
$\mathbf{a}^H$	Hermitian transposed of the vector $\mathbf{a}$
$\mathbf{A}$	matrix
$\mathbf{A}^*$	complex conjugate of the matrix $\mathbf{A}$
$\mathbf{A}^T$	transposed of the matrix $\mathbf{A}$
$\mathbf{A}^H$	Hermitian transposed of the matrix $\mathbf{A}$
$\mathbf{A}^{-1}$	Inverse of the matrix $\mathbf{A}$
$\mathbf{A}^{\#}$	Moore-Penrose pseudo-inverse of the matrix $\mathbf{A}$
$*$	convolution sum
i, k, m, n, q	indices
$x(t)$	continuous time variable
$x(n)$	discrete time variable
exp	exponential function
j	imaginary unit
diag{}	diagonal matrix of the argument vector
$\alpha(n)$	the binary data for transmission in GMSK
$\psi(t)$	continuous phase modulation pulse for GMSK
rect	rectangular function
T	transmitted symbol period in GMSK
$a_0(n), a_1(n)$	input data in linearized GMSK modulation
$p_0(n), p_1(n)$	the two significant pulses for linearized GMSK modulation
$x(n)$	output sequence in GSM
$\tilde{x}(n)$	derotated output sequence in GSM
$h(k)$	channel impulse response in GSM
$w(n)$	discrete time AWGN
$\tilde{a}(n)$	input sequence after derotation in GSM
$p(t)$	the impulse response of the pulse shape filter GSM
$c(t)$	the impulse response of the transmission channel in GSM
$r(t)$	the impulse response of the receive filter GSM
P	oversampling factor of the linearized GMSK signal
L_h	channel impulse response length
t_o	sampling phase
$h_i(n)$	the CIR of the i-th subchannel
$P_i(z)$	Z-transform of the pulse shape filter corresponding to the i-th subchannel
$C_i(z)$	Z-transform of the i-th transmission sub-channel
$R_i(z)$	Z-transform of the receive filter corresponding to the i-th subchannel

$c_k(n)$	spreading code chips of the k-th user
T_c	chip period
T_s	symbol period in DS-CDMA
N_c	spreading factor
$v(t)$	chip pulse shape filter
$\tilde{c}_k(t)$	continuous time pulse-shaped spreading code of the user k
$\mathbf{s}_{c,k}[n]$	transmitted chip sequence of the user k in the n-th symbol period
$\mathbf{c}_k[n]$	spreading code of the k-th user in the n-th symbol period
$b_k(n)$	transmitted data symbols of the k-th user in DS-CDMA
Q	the number of received antennas/oversampling factor in DS-CDMA
K	the number of users in DS-CDMA
$h_{kq}(i,n)$	the time-varying CIR from the user k to the antenna q
$w_q(n)$	AWGN at the antenna q
τ_k	the propagation delay of the k-th user
p_k	the integer part of the propagation delay for the k-th user
d_k	the fractional part of the propagation delay for the k-th user
$y_q(n)$	received signal at the q-th antenna
$\mathbf{a}_{2k}, \mathbf{a}_{2k-1}$	the propagation delays and code-word vectors for the k-th user
$\mathbf{D}(r,\alpha)$	permutation matrix
$\mathbf{A}(\tau)$	the propagation delay and code-word matrix
$\mathbf{H}$	channel matrix in short-code DS-CDMA
$\mathbf{z}[m]$	input bit sequence in short-code DS-CDMA
$\mathbf{E}_s$	signal subspace
$\mathbf{E}_n$	noise subspace
$\mathbf{R}$	output covariance matrix in short-code DS-CDMA
$\mathbf{I}_M$	identity matrix of size M
$\Vert . \Vert^2$	Squared Frobenius norm
$\mathbf{Q}$	noise plus interference covariance matrix
$\mathbf{R}_{zz}$	input correlation matrix
$\mathbf{R}_{zy}$	input-output correlation matrix
$\mathcal{J}, J$	cost functions
$\mathbf{W}$	receiver filtering matrix in short code DS-CDMA
$\mathbf{u}_1, \mathbf{U}$	the matched filer output vector/matrix of the desired user/interfering users
$\mathcal{F}\{\}$	discrete Fourier transform operator
$\theta[n], \mathbf{x}_k[n]$	parameter vectors in space-state models
$\mathbf{F}_s$	state transition matrix
$\mathbf{z}_k[n]$	process noise in state-space models
$\mathbf{w}_{k,i}[n]$	additive noise plus interference vector
$\hat{p}_k(n)$	estimated integer part of the propagation delay
$\hat{p}_k(n\vert n-1)$	predicted integer part of the propagation delay
$\mathbf{C}_i$	spreading code matrix during the i-th symbol
$\mathbf{B}_i$	transmitted bits matrix
μ_i, α	weights for PIC methods
$\rho_{k,p}$	correlation between the users k and p
$\theta_{k,p}$	weight for the correlation between the users k and p

$r_{c,k}(n)$	delayed input sequence in long-code DS-CDMA
$x_q(n)$	the received sequence at the q-th array in long-code DS-CDMA
$\mathcal{H}_q^{(k)}[n]$	time-varying channel matrix from the k-th user to the q-th antenna
$\mathcal{H}[n]$	MIMO time-varying channel matrix
M	the maximum propagation delay in long-code DS-CDMA context
	the number of subcarriers in OFDM context
B	delay matrix in long-code DS-CDMA
$C[n]$	combined delay and channel matrix in long-code DS-CDMA
$\mathcal{A}, \mathcal{A}_1$	parameter matrices of the channel dynamic model
$\mathcal{W}, \mathcal{W}_1$	process noise matrices
$tr\{\mathbf{A}\}$	trace of the matrix $\mathbf{A}$
$E\{.\}$	expected value operator
Δ, Δ_1	step-size parameters
σ_w^2	additive noise variance
σ_{max}^2	maximum transmitted power
$G[n]$	MMSE equalization matrix in long-code DS-CDMA
R_{ss}, R_{sx}, R_{xx}	input, input-output and output correlation matrices in long-code DS-CDMA
$\mathbf{e}^{(k)}[n]$	signal error vector
$W_N(k)$	windowing matrix
$\epsilon_q^{(k)}(m)$	the energy of the m-the diagonal in the channel and delay matrix
$\mathbf{v}_k[n]$	propagation delay profile in long code DS-CDMA
$\mathbf{u}[n]$	transmitted symbols in OFDM
$\mathbf{s}[n]$	OFDM modulated symbols
P	cyclic prefic length
$\mathbf{T}$	CP adding matrix
$\mathbf{F}$	DFT matrix in OFDM
ϵ	frequency offset
δ	time offset
$\mathbf{h}$	CIR vector
$\mathbf{R}_{hh}$	channel correlation matrix
$\mathbf{R}[n]$	delayed signal convolution matrix in OFDM

Chapter 1

Introduction

1.1 Motivation of the thesis

In wireless digital communications the transmitted signal is subject to various impairments and distortions caused by the transmission medium. The signal propagates through multiple paths to the receiver and usually there is no line- of-sight (LOS). The transmission medium changes its characteristics in time due to the mobility of the transmitters and/or receivers as well as the mobility of the scatterers. Therefore it is characterized by the time-varying CIR. Wireless communication channels are time, frequency and space selective, their impulse responses change as a function of time, frequency and location. The space selectivity of the channels can be exploited if multiple antenna are used at the receiver and/or transmitter. An overview of the properties of mobile wireless channels is presented in [157]. The receiver has to compensate for the distortions introduced by the channel in order to reliably detect the transmitted information bits. This operation may be performed by looking directly for the inverse system of the CIR, procedure called direct equalization. Another approach is to estimate the CIR and perform the data detection based on the channel estimate (e.g. Viterbi algorithm [132]). The channels' selectivity can be exploited as a source of diversity in order to increase receiver performance [196].

In future wireless systems the needs of high data rate services will require larger bandwidth for transmitted signals at higher carrier frequencies. Therefore, there is a high Doppler spread, making the channel time-varying within very short time periods. In this scenario the traditional equalization schemes based on the time-invariance of the channel over a certain time period may fail. Adaptive techniques that are able to track the channel time variations are preferred instead. One solution is to use decision-directed (DD) methods [11, 105, 123]. In such a scheme a channel estimation algorithm uses a training sequence to initially acquire the CIR and after that it uses the receiver data decisions to track the channel time variations. The channel estimator may lose the track if the channel time variations are very fast. A periodic training can avoid the loss of the track and it also solves the problem of the random access time of the users to the system. In order to achieve high effective data rates the amount of training data should be kept as small as possible using advanced signal processing techniques.

Blind equalization methods provide an improvement in the effective data rates, see [69, 77, 165, 174] and references therein. These methods do not require any specific training symbols to estimate the CIR or the equalizer. Instead they use the statistical and structural properties of the communication signals. Statistical information usually relies on second order cyclostationary statistics (SOCS) or higher than second order statistics (HOS). The finite alphabet and constant modulus are widely used structural properties of communications signals in blind equalization. Blind equalization techniques are used in applications such as high speed modems. Blind techniques stemming from the same theoretical basis are used in image processing and medical applications for signals separation [26, 66]. Blind equalization techniques encounter some problems: identification ambiguities, slow convergence of the estimated statistics and identification problems. The HOS based methods have high computational complexity while the SOCS based methods tend to be less complex. The inherent ambiguities may be solved using differential encoding or very small amounts of training data. Due to the relatively slow convergence, the applicability of blind equalization algorithms may be restricted to low mobility scenarios. An investigation of their performance in wireless communication systems may reveal useful information regarding the design of receivers. Even though they may not be fully applied, blind equalization methods may be combined with a trained method in order to obtained a more robust and more effective semi-blind receiver. The semi-blind methods use the statistical information from the signals as well as limited training data. Their performance usually exceeds the performance of either the training based algorithms or the blind algorithms [27].

In recent years, there has been plenty of research work on multi-antenna systems [63, 196]. By using more antennas at the receiver and/or transmitter, the network capacity and the spectral efficiency can be increased. Consequently, higher data rate services can be provided. The usage of multiple antenna in practical systems is commonly considered only for base stations, due to problems related to dimensions, power consumption and cost. The number of antennas is also limited from for the same reasons. However, mobile terminals may also be equipped with fewer antenna elements that may be co-located. Transmit antenna diversity is often used in downlink to increase link reliability. It also provides space diversity for terminals equipped with only one antenna. Transmit antenna diversity is less straightforward to exploit since a feedback path is usually needed to provide the transmitter with knowledge about the channel state information. Open-loop transmit diversity methods also exist but are less efficient. In a transmit diversity scheme the transmitter uses block or trellis space-time code to improve link reliability [6, 63, 163]. At the receiver, spatial diversity may be maximally exploited when the sub-channels from the transmitter to each receive antenna element are uncorrelated. In single user scenario, this assumption holds if the distance between the antenna elements is larger than the coherence distance [40, 133, 196]. In a multiuser scenario this assumption holds if the users are well separated in space. For high frequencies, the receive antenna diversity may also be feasible for mobile stations, since the coherence distance is small compared to the physical dimensions of the terminal. Multiantenna systems increase the spectral efficiency of the link and allow for spatial multiplexing, therefore providing a more reliable performance than single antenna systems. The price to be paid is in the increased complexity of the algorithms as well as higher equipment costs.

In asynchronous systems, the receiver also has to perform the estimation of the propagation delays. The uplink in a DS-CDMA network is asynchronous, since each active users transmit the signals independently, using the same net- work resources. Traditional uplink DS-CDMA receivers use correlation based techniques for delay estimation [129]. In realistic scenarios the correlation detectors are very sensitive to multi-user interference (MUI). Many synchronization methods have been proposed for short-code DS-CDMA in the literature [85, 151, 161, 160, 209]. These methods can not be used directly in long-code systems. Moreover, their computational complexity becomes prohibitive. Therefore, there is a need to develop channel and delay estimation methods which take into account the properties of the long-code DS-CDMA system.

OFDM is a multicarrier modulation where the transmitting data is divided into several parallel data streams and these streams are modulated onto orthogonal sub-carriers. Therefore, the high data rate frequency selective channel is split into parallel lower data rate frequency non-selective sub-channels. If a deep fade occurs in the channel at a certain frequency, only a small part of the transmitted signal is affected. The effect of the deep fade is further reduced by using a powerful error correction code. The main advantage of OFDM is the ease of implementation achieved by using Discrete Fourier Transform (DFT). Time synchronization in an OFDM transmission is a very important task since the correct DFT windowing at reception requires it. If the time synchronization error is less than the cyclic prefix (CP) length, there is no loss in the performance due to the DFT properties. If the synchronization error is larger than the length of the CP, then the loss in performance is significant. A delay estimation error of 20% of the data symbol period makes the correct detection of the symbols impossible even in the noiseless case. The equalization of the OFDM signal is usually done in the frequency domain with the inverse of the estimated channel frequency response. Therefore the channel impulse response or the channel frequency response has to be estimated.

1.2 Scope of the thesis

The scope of this thesis is to develop efficient receiver structures for wireless communication systems. The algorithms proposed in this thesis are restricted to the physical layer for fixed and mobile wireless networks. Cellular GSM-EDGE and DS-CDMA systems are considered as well as fixed wireless high data rate links based on OFDM. The proposed solutions are derived based on the minimum mean squared error (MMSE) and least squares (LS) optimality criteria.

The feasibility of blind single-user equalization methods in GSM-EDGE systems is studied in this thesis.

A receiver structure that performs channel estimation and tracking, equalization and delay estimation for an uplink asynchronous DS-CDMA is developed. These algorithms are derived for long spreading codes unlike most of the algorithms proposed in the literature, which assume short spreading codes.

An algorithm for time synchronization and channel estimation in fixed wireless OFDM transmissions is also derived.

The channels are assumed frequency selective but time non-selective for the GSM-EDGE and OFDM systems. The time stationarity is generally required by the blind equalization techniques studied for GSM-EDGE. In the fixed wireless links based on OFDM, the channels are stationary over large periods of time w.r.t. the data symbol period. In DS-CDMA systems, the channels are considered to be time and frequency selective. For algorithms derivation purposes they are modeled as a low order auto-regressive (AR) process. This approach is widely used in the literature [67, 68, 92]. In the simulations, the channels are generated according to a more realistic channel model [58].

The goal of this thesis is to develop physical layer receiver structures capable of providing a high level of performance in realistic scenarios. The algorithms should exploit any useful information or property of the communication system while achieving performance improvements over the existing methods or equal performance with a lower degree of computational complexity.

The design goal of the proposed algorithms is robust performance in the face of impairments specific to wireless communication systems: time-varying frequency selective channels, interference from the other users, asynchronism, imperfect power control and background noise. The performance studies should be as realistic as possible taking into consideration all these impairments.

1.3 Contributions of the thesis

The contributions of this thesis are in channel estimation and time synchronization for wireless communication systems. Other issues of the front-end receiver in digital communications (coding, downsampling, IQ processing etc.) are important but they fall behind the scope of this thesis. These issues will be shortly addressed when the system models are presented. For more details regarding the digital communications receiver structure, see [134].

The feasibility of blind equalization in GSM networks is investigated in this thesis. It is shown that a linearized GSM signal may be blindly equalized with fractionally spaced blind methods even though it is a band-limited signal with a low excess bandwidth. The input sequence in the linearized GSM signal is not uncorrelated and many blind equalization methods are not directly applicable. If a derotation scheme is performed on the linearized signal, it is proved that the corresponding input sequence is uncorrelated. The superior performance of the fractionally spaced equalizers is shown in simulations performed in conditions specific to GSM and its higher data rate evolution EDGE [39]. The fractionally spaced blind equalizers are applicable and deliver good results for both GSM and EDGE if the channel itself does not introduce common zeroes among the sub-channels resulting from oversampling. The CIRs are required to be time-invariant over a certain period. The risk of encountering sub-channels with common zeroes is reduced if multiple antennas are used instead of oversampling and they are well separated apart.

A novel receiver structure for the asynchronous uplink in long-code DS-CDMA is derived in this thesis. Multiple antennas are assumed to be available at the receiver. The active users transmit their signals with different propagation delays. The developed system model is characterized by a channel matrix which also includes the information of the propagation delays. An adaptive multi-user method for channel matrix estimation is derived. The estimation of this matrix leads to an implicit estimation of the CIRs and the propagation delay of each user. The explicit estimation of the integer part (multiple of the chip period) of the delays is needed for despreading. Reliable and low complexity methods for delay estimation are also proposed by exploiting the channel matrix structure. The channel estimator takes into account the dynamics of the channels. Therefore, it ensures the tracking of their time variations. The convergence in mean sense of the channel estimator is also established. The values of the tuning parameters of the adaptive channel estimator which guarantee the algorithm convergence are derived theoretically. The equalization is performed via an MMSE multi-user equalizer. The performance of the algorithms is investigated in simulations where the channels are time-varying and different background noise and multiuser interference levels are considered. The proposed receiver structure is designed for long-code CDMA unlike most of the proposed methods in the literature [9, 51, 62, 119, 183]. The synchronization of the users is performed at the receiver. The same system model is used and very low computational complexity deterministic methods are proposed. The developed receiver structure delivers the CIR for the active users, transmitted symbols and propagation delays simultaneously. The performance studies show that the proposed receiver achieve a good level of performance at low SNR, where other methods would fail (e.g. subspace methods requiring a high SNR).

A novel iterative method for joint channel estimation and time synchronization in an OFDM transmission is derived in this thesis. Burst transmission is assumed, with two known, equal OFDM symbols at the beginning, as in the fixed wireless WLAN IEEE 802.11 standard. The unknown channel and delay parameters are first roughly estimated. By iterating the algorithm on the same received data the estimates are refined. The delay estimator is robust to carrier frequency offsets caused by transmitter and receiver oscillators mismatch. The channel estimator is only sensitive to large frequency offsets. The algorithm also allows for the estimation of the frequency offset. The proposed algorithm acquires the parameters quickly with a low degree of computational complexity. The method does not require the use of the cyclic prefix from the OFDM signals unlike many proposed methods in the literature. It is a flexible solution which delivers a reliable performance at the SNR of interest.

The rest of the thesis is organized as follows. In Chapter 2 the feasibility of blind equalization for GSM-EDGE is investigated. The system model is introduced. A brief review of the blind methods proposed in the literature for GSM-EDGE is given. The author contributions to this topic are presented. In Chapter 3 the asynchronous DS-CDMA system is introduced. The signal model is developed first. Existing algorithms for propagation delay estimation and data detection are reviewed for short-code and long-code DS-CDMA. The author contributions in the receiver design for asynchronous long-code DS-CDMA are described in Chapter 4. The proposed adaptive multichannel estimator and the propagation delay estimation methods are introduced. In Chapter 5 the problem of channel estimation and time synchronization for OFDM transmission is presented. The signal model is developed and several methods proposed in the literature are reviewed. The author contribution is briefly introduced. Finally, Chapter 6 summarizes the results and the contributions of the thesis.

1.4 Summary of the publications

The material in this thesis is presented in nine publications. Two of them are related to blind equalization in GSM, six develop channel and delay estimation for long-code DS-CDMA and the last one introduces a novel channel and delay estimation method for OFDM transmissions.

In *Paper I* it is proved that the GSM signal itself does not have any properties that make the fractionally spaced (FS) blind equalization methods inapplicable. This contradicts some claims in the literature that FS blind equalizers are not feasible in GSM due to the small excess bandwidth of the signal [25, 29]. The pulse shape of the linearized signal is assumed to be the transmission filter. Sampling the pulse shape at a fraction of the symbol period does not induce common zeroes among the resulting sub-pulses. Therefore the identifiability condition of the FS blind equalizers is not violated by the signal itself. Even though the pulse shape has little excess bandwidth, it is shown in simulation that FS blind equalizers can deliver a reliable performance. Therefore, the linearized GSM signal is feasible for blind equalization.

In *Paper II* the performance of several blind equalization methods in EDGE is investigated with both linearized GMSK and 8-PSK modulated data. The input sequence of the linearized GMSK signal is not uncorrelated. Therefore, many blind equalization methods are not directly applicable. It is proved in this paper that a derotation scheme on the received signal transforms the input sequence into uncorrelated sequence without loss of performance. The superior performance of the FS blind equalizers is observed in the simulation results.

In *Paper III* the novel stochastic-gradient multichannel estimator for asynchronous long-code DS-CDMA is derived. The channels are assumed to have time variations according to a specific dynamic model. The method also includes the estimation of the channel dynamics parameters. Therefore it enables more accurate time-varying channel tracking. The algorithm is derived based on the assumption that the propagation delays of the users are known. An MMSE equalizer is also derived based on the estimated channel matrix and the statistics of transmitted and received signals. The algorithm performance is studied in face of different background noise levels and near-far effects. The low complexity adaptive channel estimator delivers a good performance for low SNR scenarios where other methods (e.g. subspace based) do not work.

In *Paper IV* a new system model is derived for the asynchronous DS-CDMA by assuming that only the maximum possible value of the propagation delays is known, but not the true values. The resulting system is characterized by a channel matrix which also includes the effect of the propagation delays. The algorithm proposed in *Paper III* is employed for the new system model to adaptively estimate the matrix of channel coefficients and propagation delays. An MMSE equalizer based on the estimated channel and delay matrix is also derived. It is observed that for despreading purposes the integer part of the propagation delay has to be estimated. The channel matrix has a special structure due to the absorption of the propagation delays information. This structure is exploited in deriving a simple but efficient delay estimation algorithm.

Paper V deals with the estimation of users propagation delays. The user delays are characterized by deterministic matrices, with a known structure. A low complexity propagation delay estimation method is developed based on the minimization of a non-linear LS cost function. The minimization is performed by evaluating the cost function on a finite number of the propagation delays (grid search). The non-linear cost function contains the estimated channels and delay matrices. Unlike most of the methods presented in the literature, this method is derived for long-code CDMA and has a low complexity. Moreover, it is robust to near-far effects.

The *Paper VI* is the main publication of the thesis. The adaptive channel estimation method proposed in *Paper IV* is thoroughly investigated. Theoretical analysis of the algorithm convergence in the mean sense is provided. The values of the tuning parameters are derived so that the convergence in the mean of the adaptive channel estimator is guaranteed. Additionally, a better delay acquisition method is proposed based on the estimated channel and delay matrix structure. The performance of the channel estimator, as well as the performance of the overall receiver structure is studied in various scenarios with different noise levels and near-far effects. This paper proposes a complete receiver structure with an adaptive channel estimator, delay estimator and an MMSE equalizer for long-code CDMA.

Paper VII introduces a new method for the integer part of the propagation delay estimation. The method is suitable for adaptive channel estimation. The channel matrix estimate obtained by the algorithm in *Paper VI* is used. The proposed solution gives a high probability of delay acquisition in very high background noise levels and MUI scenarios and with low computational complexity.

In Paper VIII the problem of the delay estimation based on the channel matrix structure is thoroughly investigated. It is proved that second order statistics of the received signal contain only partial information of the propagation delays. The large-sample properties of the method proposed in *Paper VII* are also established. It is shown that if a large number of independent channel matrix estimates are available the integer part of the propagation delays can be acquired with probability 1 in high noise level scenarios using a time averaging scheme. This paper proposes a new framework for the propagation delay estimation. It takes advantage of the fact that the fractional part of the propagation delays are estimated implicitly by estimating the channel matrix.

In *Paper IX* a novel method for the estimation of the channels and time delays in OFDM is developed. It uses a system model with two identical training symbols specific to WLAN IEEE 802.11 scenarios. Rough delay and channel estimates are obtained using non-linear LS and linear LS methods respectively. Iterating on the same received data the original estimates are significantly improved. The delay estimator is very robust to the frequency offsets, while the channel estimator is sensitive to large frequency offsets. However, the method allows for the inclusion of a frequency offset estimation step in the algorithm. This method has a low degree of complexity and simultaneously solves two problems of the WLAN OFDM based receivers: synchronization and channel estimation.

The simulation software for *Papers I* and *II* was written by the author of this thesis in cooperation with the other co-authors. The idea of proofing the applicability of fractionally spaced blind equalization to GSM in *Paper I* is based on [103]. The second author provided simulation software for a FS blind equalizer. The third author of *Papers I* and *II* provided the simulation software for generating GMSK signals. The author of this thesis did all the simulation studies presented in these two papers and also did most of the writing of *Papers I-II*. The co-authors collaborated in the design of the experiments, provided guidance for the author proofs and contributed to the writing of the final version of each paper.

The algorithms in *Papers III-IX* were derived by the author of this thesis. He wrote the simulation software used in the examples. The theoretical results presented in these papers were also established by the author. The co-author provided guidance during the development of the algorithms and suggested ideas for obtaining the theoretical and experimental results presented in the papers. He also contributed to the writing of the final version of each paper.

During his research work the author of the thesis also published other related publications which are not included in this thesis. Papers [35, 36, 37, 155, 156] deal with the estimation of time-varying channels and tracking using Kalman filtering and Decision Feedback Equalization (DFE). These papers also developed methods for the noise statistics estimation in state-space based system models. In [4] a direct blind equalizer was proposed for OFDM. Chapter [77] is a tutorial for blind channel estimation and equalization techniques for wireless communications.

Chapter 2

Blind equalization in GSM systems

2.1 Overview

GSM is a second generation cellular communication system that was developed to solve the fragmentation problems in the first cellular systems in Europe. GSM is the first commercial wireless communication system to specify digital modulation and network level architectures and services [135]. In order to respond to demands on new multimedia services, the GSM system is evolving towards higher data rates by using packet switched transmission in General Packet Radio Service (GPRS) [175] as well as higher order modulations (8-PSK) in EDGE [39].

GSM utilizes two bands of 25MHz which have been set aside for system use in all the countries which have adopted the system. In Europe the carrier frequencies are 900MHz and 1.8GHz while in the USA the carrier frequency is 1.9GHz . The available uplink and downlink frequency bands are divided into 200 kHz channels. Each frequency channel is shared by eight users, separated in time by their non-overlapping time frames. In each time frame a data burst is transmitted which consists of two 58-bit data slots and a mid-amble of 26 bits used for synchronization and channel estimation. At first glance it can be observed that more than 22% of the data in a frame is not used for transmitting information bits. Therefore, schemes that can improve the effective data-rate are of great interest.

Blind equalization methods provide attractive solutions since they do not require any known transmitted data for channel estimation and equalization purposes [69, 77, 165, 174]. Instead, they use the statistical and structural properties of the communication signals (finite alphabet, constant modulus, sub-spaces orthogonality). Channel identification or equalization requires that information about both the channel amplitude and phase responses can be acquired from the received signal. A symbol rate sampled communications signal is typically wide sense stationary (WSS). Second order statistics from a WSS process contain no phase information. Hence one can not distinguish between minimum phase and non-minimum phase channels. Therefore, other statistical properties of the signal have to be used to extract the phase information.

The communication signals are typically non-Gaussian. Hence, the HOS of the signal are non-zero and may also be exploited in equalization. HOS retain the phase information as well [86]. Early blind algorithms were either implicitly or explicitly based on HOS. In time domain, HOS are represented by higher than second order cumulants and moments. Their frequency domain counterparts obtained by multidimensional Fourier transforms are called polyspectra and moment spectra. In most HOS based equalization algorithms proposed so far polycepstrum is employed [55]. Higher order statistics and spectra may not provide a feasible approach for constructing practical equalizers. They have a large variance and consequently large sample sets are needed in order to obtain reliable channel estimates. This is a severe drawback, in particular in applications where the channel is time varying, data rates are high or low computational complexity is needed. See [174] for more details. An excellent review of different approaches to HOS based blind channel identification and equalization can be found in [46, 55, 102].

In case a multiple-output model resulting from oversampling or employing multiple receivers is used, the received signal typically possesses the cyclostationarity property, i.e. signal statistics such as the autocorrelation function are periodic. Gardner discovered in [41] the fact that non-minimum phase channel equalization/identification may be obtained from the SOCS of the received signal because the cyclic autocorrelation function preserves the phase information. Hence, smaller sample sizes than for HOS are required for the convergence of the estimated statistics. The main drawback is that some channel types may not be identified, see [95]. In particular, the channel cannot be identified if the sub-channels resulting from oversampling share common zeroes. If the mutiple-output model is obtained by using an antenna array at the receiver with antenna elements well separated this limitation is less severe. This is because the resulted sub-channels are uncorrelated.

The channel impulse responses can be blindly identified and equalized under certain conditions, usually up to a complex scalar ambiguity. The identification conditions, the inherent ambiguities as well as the slow convergence, may limit the applicability of blind equalization methods in practical communication systems. Because of their high potential in providing higher effective data rates it is of great interest to study their feasibility in particular communication systems. Using a limited number of training symbols may solve their problems. Limited training data in conjunction with blind algorithms leads to semi-blind methods. Semi-blind methods are a more feasible solution for practical communication systems since they combine the benefits of both training based and blind methods. They usually achieve better performance than the traditional training based algorithms whilst using a smaller amount of training data [27]. They have a larger sample support, since both known symbols and statistical information are used. Consequently they exhibit a lower variance of the estimates.

In this chapter the feasibility of blind equalization methods is evaluated for GSM as well as EDGE. SOCS based methods are considered due to their faster convergence and reduced complexity. HOS based blind methods that are more complex and have a slower convergence are briely considered as well.

Blind equalization algorithms are typically designed for linear modulations, like Quadrature Amplitude Modulations (QAM). The channels are assumed to be stationary over the observation interval in order to achieve the convergence of the statistics. The received baseband signal from a channel with the composite impulse response $h(t)$ can be written as:

$$y(t) = \sum_{k=-\infty}^{\infty} a(k)h(t-kT) + w(t), \qquad a(k) \in \mathcal{A}, \tag{2.1}$$

where T is the symbol period and $\mathcal{A}$ is the input constellation set. It is assumed that the input sequence $a(k)$ is independent identically distributed (i.i.d.) while the noise $w(t)$ is wide sense stationary, white and independent of the input sequence but not necessarily Gaussian. The composite channel impulse response $h(t)$ contains the transmit and receive filters as well as the physical channel impulse response. In GSM, a non-linear GMSK modulation is used [136]. The information bits are used to modulate the frequency of a complex amplitude carrier which is shifted between two values corresponding to the transmitted 0 and 1 bits. The signal frequency domain side-lobe levels are reduced using baseband Gaussian pulse shaping. Therefore, the direct application of the linear blind equalization schemes may not be feasible. In general, when blind equalization is considered for GSM, a linear approximation of the GMSK signal is performed first [19, 30, 84, 169]. The linear approximation of the GMSK signal is introduced in the following subsection. Then, the SOCS and HOS based blind methods proposed in the literature for GSM-EDGE are briefly reviewed. In the final subsections, the author contributions to the GSM-EDGE blind channel estimation and equalization problem are introduced and some concluding remarks are drawn.

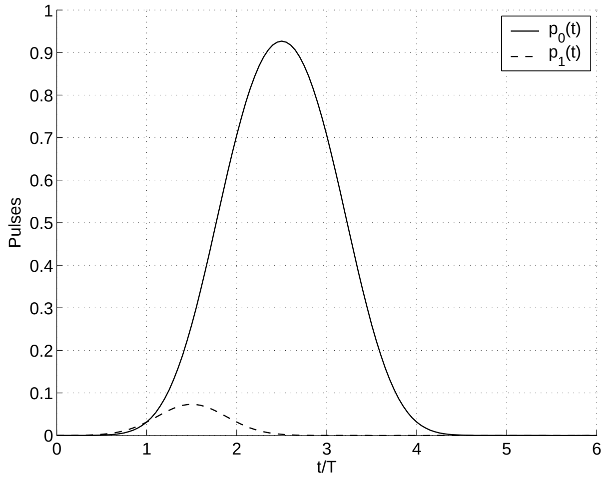

Figure 2.1: Two significant pulses in the GMSK linear approximation.

2.2 Linear approximation of the GMSK modulated signals

The baseband GMSK signal is given by:

$$s(t) = \exp\left[j\frac{\pi}{2} \sum_{n=-\infty}^{\infty} \alpha(n)\psi(t-nT) \right] \tag{2.2}$$

where $\alpha(n)$ is the binary data for transmission. The continuous phase modulation pulse $\psi(t)$ is given by:

$$\begin{aligned} \psi(t) &= \int_{-\infty}^{t} c(\tau - 2T) \\ c(t) &= g(t) * \mathrm{rect}(t/T) \\ \mathrm{rect}(t/T) &= \begin{cases} 1/T, & |t| \leq T/2 \\ 0, & |t| > T/2 \end{cases} \\ g(t) &= B\sqrt{\frac{2\pi}{\ln 2}} \exp\left[-\frac{2\pi^2 B^2 t^2}{\ln 2} \right]. \end{aligned} \tag{2.3}$$

$$\tag{2.4}$$

The excess bandwidth parameter B is set to 0.3 in GSM so that:

$$\psi(t) \approx \begin{cases} 0, & t \leq 0; \\ 1, & t \geq 4T. \end{cases} \tag{2.5}$$

The GMSK signal (2.2) can be approximated with a sum of 16 terms, each of them constituting a linear QAM signal [30]. Among the 16 different pulses only two pulses are significant while the others are nearly zero. In Figure 2.2 the two most significant pulses are illustrated.

Retaining the two most significant pulses, the linear approximation for GMSK signal with $B = 0.3$ excess bandwidth can be written as:

$$s(t) = \sum_{n=-\infty}^{\infty} a_0(n)p_0(t-nT) + \sum_{n=-\infty}^{\infty} a_1(n)p_1(t-nT), \tag{2.6}$$

where $p_0(t)$ and $p_1(t)$ are the most two significant pulses and:

$$\begin{aligned} a_0(n) &= \exp\left(j\frac{\pi}{2}\sum_{k=-\infty}^{n}\alpha(k)\right) = j\alpha(n)a_0(n-1) \\ a_1(n) &= j\alpha(n)\exp\left(j\frac{\pi}{2}\sum_{k=-\infty}^{n-2}\alpha(k)\right) = j\alpha(n)a_0(n-2), \end{aligned} \tag{2.7}$$

More than 99% of the approximated GMSK signal energy is contained in the $p_0(t)$ pulse, therefore the signal can be further simplified taking into account only the first term in the approximation (2.6).

$$s(t) \approx \sum_{n=-\infty}^{\infty} a(n)p_0(t-nT), \tag{2.8}$$

where

$$p_0(t) = \beta(t-T)\beta(t-2T)\beta(3T-t)\beta(4T-t), \tag{2.9}$$

$$\beta(t) = \cos\left[\frac{\pi}{2}\psi(t)\right]. \tag{2.10}$$

The approximation error of the true GMSK signal can be viewed as additive interference. The interference increases as fewer pulses are used in the GMSK approximation. The maximum achievable signal to interference ratio in the approximation using only the main pulse is 23 dB even in the noiseless case [208].

Having the linear approximation of the GMSK signal, linear blind equalization methods may be applied. In the next sections we present several blind equalizers for GSM based on the SOCS as well as the HOS.

2.3 SOCS based blind equalization for GSM

The baseband signal is modulated on a carrier with frequency ω_c and transmitted through the communication channel. At receiver, the signal is first down converted and then sampled with a certain sampling frequency usually higher than the symbol rate.

The linearized GMSK signal has special characteristics that have to be considered when blind equalization is employed. The pulse shape p_0 and therefore the linearized GMSK signal has little excess bandwidth beyond the $1/2T$ limit, that is 30%. Oversampling with a rate higher than $1/T$ may not generate sufficient diversity for blind equalization.

In [30], and later in [169], the required diversity is obtained using a simple derotation scheme on the received signal and then the I-Q branches are viewed as separate sub-channels. The sequence $a(n) = j\alpha(n)a(n-1)$ is a pseudo- quaternary phase shift keying (QPSK) sequence because at any given time instance, $a(n)$ can only take two values instead of four. This sequence can be also written as $a(n) = j^n\tilde{a}(n)$ where $\tilde{a}(n) = \pm 1$ is a binary phase shift keying (BPSK) sequence. With this definition, the received symbol rate sampled sequence is given by:

$$x(n) = \sum_{k=-\infty}^{\infty} h(k)j^{n-k}\tilde{a}(n-k) + w(n) = j^n \sum_{k=-\infty}^{\infty}\left[h(k)j^{-k}\right]\tilde{a}(n-k) + w(n). \tag{2.11}$$

At the receiver end, the baud sampled signal is first derotated:

$$\tilde{x}(n) = j^{-n}x(n) = \sum_{k=-\infty}^{\infty} \left[h(k)j^{-k}\right] \tilde{a}(n-k) + j^{-n}w(n). \tag{2.12}$$

Because $\tilde{a}(n)$ is a real sequence we obtain two subchannel outputs by taking the real and the imaginary part of the received derotated sequence.

$$\begin{aligned} x_1(n) &= \Re\{\tilde{x}(n)\} = \sum_{k=-\infty}^{\infty} \Re\left\{\left[h(k)j^{-k}\right]\right\} \tilde{a}(n-k) + \Re\left\{\left[j^{-n}w(n)\right]\right\} \\ x_2(n) &= \Im\{\tilde{x}(n)\} = \sum_{k=-\infty}^{\infty} \Im\left\{\left[h(k)j^{-k}\right]\right\} \tilde{a}(n-k) + \Im\left\{\left[j^{-n}w(n)\right]\right\} \end{aligned}$$

The derotation scheme results in a single-input-multiple-output (SIMO) model that also contains the channel phase information and therefore can be used in blind equalization.

In [30] several blind equalization as well as blind channel identification and maximum likelihood sequence estimation (MLSE) schemes based on the derotation scheme are compared. Two of them are blind channel estimation methods based on SOCS while the other two are direct HOS based blind equalizers. The channels are assumed to be time invariant during each GSM frame. The COST 207 wide sense station- ary uncorrelated scattering (WSSUS) channel model [58] is used to generate the channels. The necessary identification condition for the two subchannels resulting from derotation is given as well. Among the direct equalizers, constant modulus algorithm (CMA) [47] gives the best performance. The other algorithms are sensitive to channel order estimation. The non-linear blind equalizers based on SOCS blind channel identification and MLSE perform worse than the linear HOS based equalizers and the traditional trained equalization method. The loss in performance is due to the sensitivity of the adopted blind SOCS method to the channel order mismatch.

When the subchannels in a single-input multiple-output (SIMO) model share common zeroes, the SOCS based blind equalization algorithms fail. In cases where multiple antenna are used this is less likely to happen. When the derotation scheme is used, the subchannels are produced by taking the real and imaginary part of the transmission CIR. Therefore, the risk of encountering common zeroes is low. Li and Ding propose in [84] a semi-blind approach to equalization for GSM. The main idea is that we can use some of the training symbols as well as the SOCS from the output signal to get rid of the identifiability and ambiguity problems. Channel diversity is obtained using the derotation scheme. There are two important advantages to semi-blind equalizers: the training sequence can be 10 bits shorter than in the standard one and they achieve better performance in the presence of channel order mismatch and sub-channel common zeroes.

Based on the same GMSK signal linear approximation and derotation approach as in [30], Trigui and Slock derive performance bounds for co-channel interference cancellation in GSM [169]. They show that whenever the number of channels is equal to or larger than the number of users, the single-user MLSE which takes the spatio-temporal correlation structure of the interferes correctly into account, suffers a bounded matched filter loss.

2.4 HOS based blind equalization for GSM

The HOS statistics can be used for blind channel identification and equalization since the communication signals are generally non-Gaussian. In blind equalization algorithms, the HOS are represented by higher than second order cumulants and moments in time

	SOCS	HOS
Identifiability conditions	Coprime sub-channels	Non-Gaussian signals
Performance	Fast convergence, some sensitive to the channel order mismatch	Slower convergence, robust to channel order mismatch
Complexity	Medium to low	High

Table 2.1: Comparison of the SOCS and HOS based methods for blind equalization in GSM

domain and their corresponding polyspectra and moment spectra in frequency domain. Polycepstrum is employed in most of the HOS based blind equalization methods [12, 53, 122].

A comprehensive study of the reliability of HOS based blind equalizers to GSM is given in [19]. They compare the performance of two blind channel estimators (Eigen Vector approach to blind Identification (EVI) [18] and W-slice (WS) [38]) with that of two non-blind techniques (least square and cross-correlation based). For the blind techniques a data burst only contains 142 data bits, without a training sequence. A standard GSM burst with a mid amble of 26 training bits is considered for the non-blind techniques. The channels are considered to be time invariant over a data burst duration, and they are generated according to [58]. The experimental results show that the blind channel estimator EVI leads to an average 1.2 - 1.3 dB SNR loss in comparison to the least square solution. Furthermore, its performance remains unaffected by the co-channel interferences at signal to interference ratios (SIR) larger than 10 dB.

An improved blind channel estimation method for GSM using EVI is proposed in [72]. A technique similar to turbo coding is used to iteratively improve the channel estimate obtained by the blind method. It also solves the complex scalar ambiguity inherent in all blind channel estimation approaches. For this purpose the received sequence is filtered with an MMSE equalizer obtained from the estimated channels. The complex ambiguity factor is obtained by averaging the filtered signal over one data burst. The complex factor is found up to a phase ambiguity of π due to the transmitted BPSK symbols. The absolute phase can be computed if one reference symbol is available.

A different approach that uses HOS for blind equalization in GSM is proposed in [208]. For an multiple-input multiple-output (MIMO) system, a fractional sampling method is proposed which transforms the input-output relationship into an instantaneous mixture. Therefore, HOS based blind source separation methods are applied on the resulting system in order to recover the transmitted information symbols. This technique is restricted to channels with a short impulse response, since the required oversampling factor increases with the channel length.

In general the estimated HOS have high variance compared to SOCS. Therefore, the HOS based blind equalizers converge slowly. They usually need the whole GSM data burst to converge. In a real case scenario, where the channel changes from burst to burst, the HOS based algorithms may not deliver a reliable performance.

A comparison of the SOCS and HOS based approaches to blind channel identification and equalization for GSM is presented in Table 2.1.

2.5 Feasibility of blind equalization in GSM-EDGE systems

In this section the applicability of the blind equalization techniques in GSM- EDGE systems is studied. In particular, FS blind equalizers are considered due to their fast convergence and reduced complexity. We start by presenting the general assumptions and the models used in the algorithms design and the performance studies.

- In the algorithm derivation we assume that the data bearing signals are modulated using linear approximation of the GMSK. For the algorithms performance evaluation, true GMSK signals are used instead.
- The channels are frequency selective channels, time-invariant over the observation interval. The stationarity assumption is needed by majority of the blind equalization techniques.
- The additive noise is i.i.d. Gaussian distributed with zero mean and with known variance.
- The co-channel interference is considered to be 0.
- The transmitted data, the additive noise and the channels are statistically independent.

In the literature, fractional sampling of a GSM signal is sometimes deemed unfeasible in producing the diversity needed for SOCS blind equalization, [29]. The claim is justified using the results of [25], which states that a band-limited system cannot be uniquely identified from FS-SOCS. Due to its low excess bandwidth (30%), GSM is sometimes viewed as an example of such a system. The rationale is questioned in [127]. It is proved in this subsection that the FS-SOCS blind algorithms are applicable to GSM systems.

It was shown in [25] that for any band-limited system, FS-SOCS are not sufficient for blind identification. This seems to conflict with any radio communication system specification where frequency masks dictate the allowed band for each channel. The theorem is given for the identifiability of a strictly band- limited system with an infinite time-span. It is not derived for a finite impulse response (FIR) approximation of a communication channel, as is noted for example in [138]. For FIR channels the identifiability condition is well known: the subchannels of the SIMO model must be coprime [94].

The next area to consider is the issue of blind identifiability from the GSM viewpoint. It is necessary to find out whether there is a chance of non-identifiability when using the GMSK signal with 30% excess bandwidth. The composite communication channel consists of the pulse shaping filter $p(t)$ in the transmitter, the propagation channel $c(t)$ and the receive filter $r(t)$. The overall channel response is the convolution

$$h(t) = p(t) * c(t) * r(t). \tag{2.13}$$

Only the transmit filter $p(t)$ is affected by the GMSK signal waveform. At the system level it may affect the choice of $r(t)$ as well, but for simplicity it is assumed that the channel $c(t)$ and the receive filter $r(t)$ are the same for all modulation types. For GMSK, a linear approximation needs to be assumed (see Section 2.2) so that the main pulse $p_0(t)$ can be used as the transmit pulse shape.

When P samples per symbol are available at the receiver, a SIMO model can then be considered. The i-th subchannel ($i = 0, \ldots, P-1$) of $h(t)$ is denoted by:

$$h_i(n) = h(nT + iT/P), n = 0, \ldots, L_h - 1 \tag{2.14}$$

where L_h is the channel length. The Z-transform of $h_i(n)$ is then

$$\mathcal{Z}[h_i(n)] = \sum_{n=0}^{L_h-1} h_i(n)z^{-n} = P_i(z)C_i(z)R_i(z). \tag{2.15}$$

If any particular modulation type is to induce FS-SOCS identifiability problems, common zeroes among the subchannels $P_i(z)$ should appear. The linearized GMSK pulse $p_0(t)$ with 30% excess bandwidth is taken to be the transmit pulse shape. Sampling this pulse with $P = 2$ results in two sub-pulses: $p_{0,1}(n) = p_0(t_0 + nT)$ and $p_{0,2}(n) = p_0(t_0 + (n + 1/2)T)$, where t_0 is the sampling phase. These sub-pulses do not share any common zeroes regardless of the sampling phase. The channel identifiability problems may only arise from the propagation channel, provided that the receive filter is properly chosen. The simulation results presented in *Paper I* show that the excess bandwidth (30%) of the GSM signal is sufficient to achieve blind equalization. This is in contrast to some previous results, e.g. [168]. The performance of two blind equalization methods is also evaluated: the FS version of the CMA algorithm and the blind MMSE algorithm proposed in [153]. The inherent ambiguities in the blind equalization are solved by means of differential encoding. In simulations the true GMSK modulated signals have been used.

The performance measure of the algorithms is the mean squared error (MSE) of the equalized sequence. It is chosen because the employed algorithms estimate directly the inverse of the channel impulse response. The raw symbol error rate (SER) performance is directly related to the MSE. The simulations conditions and results are presented and discussed in *Papers I-II.*

Many blind algorithms exploit the fact that the input sequence is white [45, 111, 153]. The colored signals cannot be equalized using these methods, since the algorithms derivation depends on the whiteness assumption of the input signals. It is shown in [103] that most of the error correction coding methods do not destroy the whiteness of the communication signals. Interleaving randomizes the communication signals even more. The transmitted symbols of the linearized GMSK signal are not white. They are given by $a(n) = j\alpha(n)a(n-1)$, where $\alpha(n)$ are the transmitted binary data. In order for it to be applicable for all blind equalization methods, the input sequence has to be white. The method based on the Markov models for the description of the signals [14, 103] is employed in *Paper II* to show that the derotated linearized GMSK signal is uncorrelated if the transmitted binary data sequence is also uncorrelated (achievable via good source coding). The FS version of the CMA algorithm as well as the FS blind equalizer of [153] are employed in the EDGE transmission scenario with both linear-GMSK and 8-PSK modulations. Their performance is compared to the HOS blind channel estimation algorithm of [18]. The MSE performance of the equalized sequence is presented for the direct blind equalizers in order to study their convergence speed. The performance of [18] is studied by employing the Viterbi algorithm on the blindly estimated channels. Therefore, the raw SER was used as a performance indicator for all three algorithms. The results of the simulations indicate the superiority of the FS methods compared to the HOS approach.

2.6 Concluding remarks

In order to apply blind equalization in practical GSM-EDGE receivers, the following problems need to be solved:

- The SOCS based blind equalizers cannot equalize subchannels sharing common zeroes.

- The estimated HOS have high variance. Therefore, they converge more slowly than SOCS and need more data samples. The best of these need an entire GSM data frame to converge.

The pulse shape of the linearized GMSK modulation does not introduce identification problems for the FS-SOCS blind equalizers. If multiple-antennas are used at the receiver, and they are more than the coherence distance apart, the risk of encountering common zeroes among the sub-channels is very low. Therefore, it is preferable to use multiple antennas instead of oversampling, when FS-SOCS based blind equalizers are employed.

The slow convergence of the HOS may be another source of impairment in a realistic scenario. In high mobility scenarios the time variations of the channels are very fast. In this situation the coherence time of the channels is less than the convergence time of the blind HOS based algorithms. Therefore, the system conditions change continuously and the blind equalizer can not achieve a reliable performance. In low mobility mobile communications and fixed wireless or wired communications the channels change slowly. They can be considered stationary over a certain time period. In this case, blind equalization techniques may be successfully applied. For example, the CMA algorithm is applied in high speed modems [167].

Due to their reduced complexity and faster convergence, the FS-SOCS based blind equalizers are a more feasible solution for GSM-EDGE than the HOS methods.

The GSM standard has been enhanced to allow higher data rates and to provide improved quality of service, by allocating a larger bandwidth (e.g. PCS-1900) or by using higher order modulations (8-PSK in EDGE) at higher carrier frequencies. The equalization task becomes more difficult since the Doppler spread increases, making the channels time-variant even within a data burst. Higher output SNR and higher quality channel estimates have to be ensured in order to deal with higher order constellations, such as 8-PSK. Training sequence based channel estimation and equalization methods perform the parameter estimation using only the known symbols in the training sequence. Useful information which may be contained in unknown data symbols is ignored. Blind methods are based on the knowledge of the structural and statistical properties of the transmitted data, but not on explicit knowledge of the input symbols. Semi-blind techniques combine the information contained in a few known symbols with the statistical and structural properties of the communication signals [27]. The knowledge of a small number of training symbols allows resolving the blind methods ambiguities. Moreover, all the channel types become identifiable. Semi-blind techniques are very appealing techniques from the performance point of view. Their performance is superior to that of either training based techniques or blind techniques [27]. Semi-blind methods may be applicable when blind methods alone fail, in estimating and tracking time varying channels. They use less training data than the training only methods and truly combine the statistical information of the signals with the known symbols [27].

Chapter 3

Receiver algorithms for asynchronous DS-CDMA

The key concept in the multiple access techniques in the communications systems is the orthogonality: in Time Division Multiple Access (TDMA) due to different time slots, in Frequency Division Multiple Access (FDMA) due to different frequency slots. CDMA is a multiple access technique where the separation of users is done neither in frequency, nor in time, but rather through the use of the codes. The manner in which the network resources are allocated in CDMA systems is depicted in Figure 3.1.

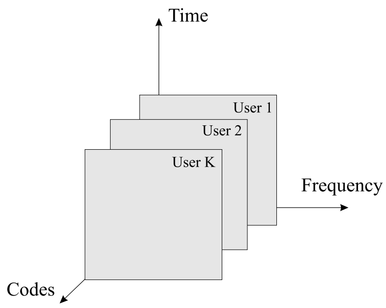

Figure 3.1: The network resources allocation in CDMA systems.

The roots of CDMA date back to the 20's [150]. This technology was mainly used in military applications due to its resistance to interference and intentional jamming and due to increased link security. Several types of CDMA exist, the two main types being Frequency-Hopping CDMA (FH-CDMA) and Direct-Sequence CDMA (DS-CDMA).

In FH-CDMA each user transmits its data on one frequency band. During the data transmission the transmitter hops between different frequencies according to a pseudo-random hopping pattern. The receiver hops synchronously with the transmitter, using the same hopping pattern. There are two types of frequency hopping: fast (the frequency is changed during a single data symbol) and slow (several symbols are transmitted on the same frequency). The FH-CDMA multiple access is based on the idea that different users use different frequency hopping patterns at the same time moments. The hopping patterns are orthogonal, i.e. the users do not use simultaneously the same frequency for transmission

The other main type of CDMA is DS-CDMA, in which each user is assigned a unique code sequence which is multiplied with the data before transmission, operation called spreading. The information bits are recovered by multiplying the spreaded sequence with the corresponding code. The spreading-despreading operations are illustrated in Figure 3.2. The spreading factor or processing gain is defined as the ratio of the code bandwidth

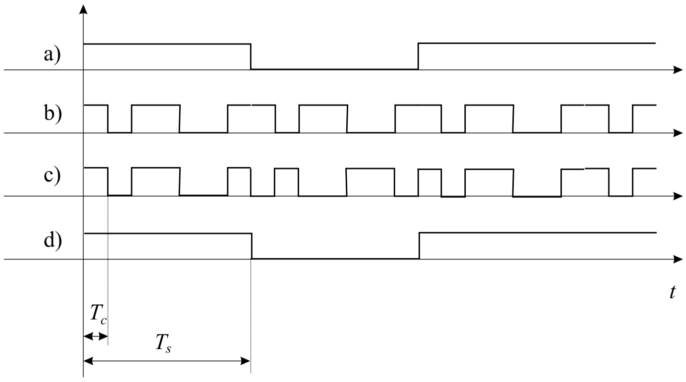

Figure 3.2: The direct sequence spreading-despreading. a) the information bits sequence with bit period T_s, b) the spreading code with the chip period T_c, c) the resulting sequence after spreading and d) the recovered data bits after despreading.

versus information signal bandwidth, $N_c = \frac{T_s}{T_c}$. The spreading code may have a period equal to the symbol period, the so-called short-code, or the period may be much longer than the symbol period, the so-called long-code.

Both types of CDMA will result in transmitting signals where the bandwidth is larger than the data sequence bandwidth . CDMA systems are often referred as spread-spectrum systems. A good introduction to CDMA systems can be found in [129] and a historical survey in [150]. Text-books on spread-spectrum communications are [32, 154] and in [3] a collection of several papers regarding CDMA can be found.

DS-CDMA has been adopted by many of the modern wireless communication systems as the physical layer technique. It is used already in IS-95 and cdma2000 networks developed by the Qualcomm Corp., and is the main radio interface for 3G proposals [1, 60, 164]. Among the many advantages of the CDMA that can be highlighted is the increased network capacity, increased data rates and the possibility it offers in accommodating services with different data rates [121].

In CDMA based networks the downlink (forward link) and uplink (reverse link) connections are different. In the downlink the base station transmits signals to the active users in the cell in a synchronized manner. In the uplink different users sharing the same bandwidth and time slots transmit their signals to the base station on different channels and with different delays. Therefore, the uplink CDMA is asynchronous. Consequently the uplink receiver algorithms have a higher degree of complexity than the downlink receivers. They also have to deal with the synchronization as well. In general, an uplink receiver, has to perform the operations illustrated in Figure 3.3.

The received input signal is the sum of all the signals from the asynchronous active users, received with different powers and distorted by the corresponding channels. Background noise is also added to the received signal. The receiver has to estimate the channel for each user as well as the corresponding propagation delay. These two operations usually interact with each other. Using the estimated parameters, an equalization method is applied to reduce both the inter-symbol interference (ISI) and MUI. The equalization can operate at chip level and in this case it is followed by a despreading stage. It can also operate at symbol level and in this situation the despreading is implicit. The data decision is performed on the resulting equalized signal. If necessary, the data decisions may be feed

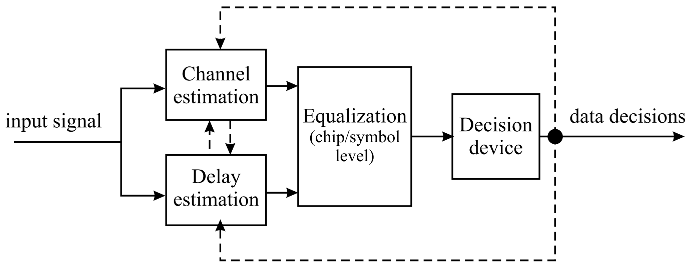

Figure 3.3: The uplink CDMA receiver

back to the channel and delay estimators.

In this chapter the asynchronous CDMA system model is described first. Then methods for delay estimation as well as receiver algorithms are reviewed. The emphasis is on methods applicable to long-code CDMA but algorithms designed for short-code CDMA are also discussed.

3.1 The asynchronous DS-CDMA system model

3.1.1 The transmitted signals

Firstly, the uplink in a DS-CDMA network cell is considered, having K active users as is illustrated in Figure 3.4. The network controlling system allocates an unique spreading

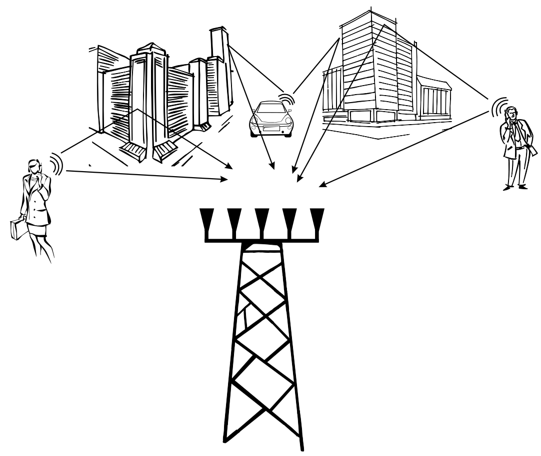

Figure 3.4: The uplink in mobile communication system

code to each user. The chip sequence corresponding to the k-th user is given by:

$$\begin{aligned} \mathbf{s}_{c,k}[m] &= \mathbf{c}_k[m] b_k(m), \\ \mathbf{c}_k[m] &= \left[c_k((m-1)N_c+1), \ldots, c_k(mN_c)\right]^T, \end{aligned} \tag{3.1}$$

where $b_k(m)$ are the information symbols of the k-th user and $c_k(n)$ is the spreading code allocated to the k-th user. The vector $\mathbf{c}_k[m]$ is referred to as the code-word of the k-th user for the m-th data symbol. If the spreading code has a period equal to the spreading factor N_c (short code), then the code-word is the same for each information symbol and the index m can be dropped. If the spreading code has a much longer period than the spreading factor (long code), then the code-word is different for different information bits.

Usually the spreading codes are first pulse-shaped with a band limited pulse. The resulting spreading code waveform for the m-th data symbol of the k-th user may be written as:

$$\begin{aligned} \tilde{c}_{k,m}(t) &= \textstyle\sum_{n=0}^{N_c-1} c_{k,m}(n)v(t-nT_c), \\ c_{k,m}(n) &= c_k((m-1)N_c+n), \end{aligned} \tag{3.2}$$

where $v(t)$ is the pulse-shaping filter impulse response and T_c is the chip period. The users share the same frequency band and time and they are separated by the spreading codes.

The spreading code of a particular user should be orthogonal to the spreading codes of all the other users. The Walsh-Hadamard codes satisfy this property, but they can only be used when a small number of users are considered. The codes orthogonality is destroyed by the asynchronous transmission and the chip pulse-shaping. Moreover, the orthogonality of the codes is reduced due to the multipath propagation. In uplink, the loss of orthogonality is more critical than in downlink due to the different channels on which the signals propagate. A thorough tutorial describing the properties of the spreading codes can be found in [145].

The continuous time DS-CDMA chip waveform of the k-th user is given by:

$$s_{c,k}(t) = \sum_{m=1}^{N_s} b_k(m)\tilde{c}_{k,m}(t-mT_s), \tag{3.3}$$

where $b_k(m)$ are the information bits transmitted by the k-th user, T_s is the symbol period and N_s is the total number of transmitted symbols by the k-th user. For the sake of simplicity we assume that the users transmit the same number of symbols.

3.1.2 Multiantenna receiver

At the BS multiple antenna may be employed to increase receiver performance. Using multiple antenna elements, the receiver can take advantage of the increased SNR. In a multiuser scenario the sub-channels from the users to the each antenna element can be considered to be uncorrelated if the users are well separated apart. Taking into account the uncorrelated sub-channels, the receiver performance can be significantly improved by using different antenna diversity techniques [130]. Multiple copies of the same transmitted signal, but distorted by uncorrelated sub-channels are available. Therefore, if a deep fade occurs on one sub-channel the useful signal can still be recovered since the risk of having a deep fade on the other sub-channels is very low. The usage of multiple antennas is feasible at the BS. It is difficult to use multiple antennas in mobile terminals due to the their reduced dimensions and for power consumption reasons. However, small antenna arrays or co-located antennas could also be used in mobile stations. The advantages of multiple antenna bring clear improvements in the performance of wireless systems. They take advantage of the spatial diversity therefore improving the link reliability, as well as the spatial multiplexing improving the spectral efficiency of the link. Multiantenna techniques are being considered in the evolution of the third generation wireless systems standards [1, 60].

In this thesis we assume that sub-channels from the users to the antennas are uncorrelated. A similar signal model is obtained if the output of a single received antenna is sampled at the rate of QT_c.

The continuous-time signals $s_{c,k}(t)$ are modulated onto a carrier with the frequency ω_c. Then, they are transmitted to the BS equipped with Q receive antennas via time-varying Rayleigh fading channels with the CIRs $h_{k,q}(\eta, t)$, $k = 1, \ldots, K$ and $q = 1, \ldots, Q$. The

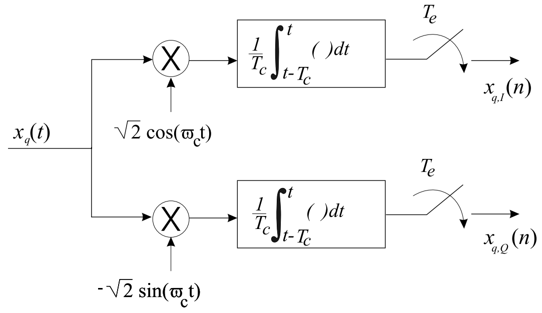

Figure 3.5: The receiver front-end. T_e is the sampling period.

CIRs are the convolution of the chip pulse-shape filter, physical channels and the receive filter. At each receive antenna the signal is corrupted by i.i.d. white Gaussian noise $w_q(t)$ with zero mean and variance σ_w^2. We assume also that the noise, data signal and the channels are statistically independent. We consider that the time-varying sub-channels from the K users to the Q antennas have the maximum delay spread of $L_h T_c$. The receiver front-end consists of a standard IQ-mixing stage followed by an integrate-and-dump filter as shown in Figure 3.5.

Taking into account the users asynchronism, the complex base-band received signal at the antenna q is given by:

$$x_q(t) = \sum_{k=1}^{K} \left(\int_{\eta} h_{k,q}(\eta, t) s_{c,k}(t - \eta - \tau_k T_c) d\eta \right) + w_q(t), \tag{3.4}$$

where $\tau_k T_c$ is the propagation delay corresponding to the k-th user.

We assume that the sampling period is equal to the chip period T_c at each antenna. Sampling the Q antennas at the chip rate is equivalent with oversampling a single antenna at the rate of QT_c. However, using multiple antenna at the receiver brings SNR and diversity gains. The equivalent base-band complex received sequence at the antenna q may be written as:

$$x_q(n) = x_{q,I}(n) + j x_{q,Q}(n) = \sum_{k=1}^{K} \sum_{i=0}^{L_h-1} h_{kq}(i, n) s_{c,k}(n - i - \tau_k) + w_q(n). \tag{3.5}$$

In Equation (3.5), $s_{c,k}(n - i - \tau_k)$ is a notational procedure to represent the delayed chip sequence of the k-th user.

The active users share the same bandwidth and time therefore in the DS-CDMA the MUI is a major source of impairment. Considering the first user as the user of interest, we can rewrite the Equation (3.5) as:

$$\begin{aligned} x_q(n) &= \sum_{i=0}^{L_h-1} h_{1q}(i, n) s_{c,1}(n - i - \tau_1) + \sum_{k=2}^{K} \sum_{i=0}^{L_h-1} h_{kq}(i, n) s_{c,k}(n - i - \tau_k) + w_q(n) = \\ &= x_q^{(1)}(n) + x_q^{(MUI)}(n) + w_q(n), \end{aligned} \tag{3.6}$$

where $x_q^{(MUI)}(n)$ is the MUI for the user of interest. In classical approaches [129, 131] the interference plus noise is characterized as Gaussian. This assumption is justified with the central limit theorem, but is usually not valid in practice. Consequently, the traditional DS-CDMA receivers [131] are very sensitive to the MUI.

For a reliable data detection, the receiver algorithm has to estimate the users' CIRs both in the downlink and the uplink. Due to the users' asynchronism, the uplink receiver has to estimate the propagation delays as an additional task.

There are different approaches to further developing the equation (3.5), depending on the type of spreading codes, the CIR and the propagation delays. In the next sections of this chapter existing receiver algorithms from literature for both short and long-codes are presented. The system model characteristics of each of the two approaches will be discussed at the beginning of each corresponding section.

3.2 Receiver structures for short-code DS-CDMA

Short-code DS-CDMA systems have been thoroughly studied and they continue to be the subject of active research topics [9, 10, 161, 183, 187, 192]. The majority of receiver structures for DS-CDMA proposed in the literature are based on the periodic spreading codes assumption. Even though the scope of this thesis is limited to developing receiver structures for long-code systems, a presentation of the most important research trends and algorithms for short-code systems will help the reader to clearly understand the advantages and disadvantages of both systems. In fact, short-code system algorithms have introduced valuable concepts which may be exploited when long spreading codes are used. There are applications where short-codes are used, such as Global Positioning Systems (GPS). Short spreading codes (C/A codes) are used here to estimate a coarse timing offset between the transmitter and the receiver [73]. However, in existing CDMA based wireless communications systems the long-codes are used exclusively as a consequence of their robustness [164]. The long-codes DS-CDMA can tolerate all manner of channel impairments while attaining high level of bandwidth utilization. The capacity of the long-code DS-CDMA system is limited by the total power of the interference and not by the number of interfering users. In short-code DS-CDMA the users with the same received power attain unequal performance [181].

In the sequel the system model specific to short-code CDMA is presented and then the main algorithms for delay estimation and data detection are briefly reviewed.

Firstly, a simple case where the channels are stationary flat fading is considered. Therefore the system model from (3.5) can be rewritten as:

$$x(n) = \sum_{k=1}^{K} h_k s_{c,k}(n - \tau_k) + w(n). \tag{3.7}$$

The extension of the system model to frequency selective fading channels is straightforward [160]. It is assumed that the output signal is oversampled by a factor of Q (or sampled at the chip rate at the Q receive antennas). The received vector on the m-th bit interval, $\mathbf{x}[m]$ of size $(QN_c \times 1)$, and the corresponding noise vector $\mathbf{w}[m]$ of size $(QN_c \times 1)$, may be written as:

$$\mathbf{x}[m] = [x(mQN_c + QN_c), \ldots, x(mQN_c + 1)]^T, \tag{3.8}$$
$$\mathbf{w}[m] = [w(mQN_c + QN_c), \ldots, w(mQN_c + 1)]^T. \tag{3.9}$$

Assuming the chip pulse shape is rectangular, the contribution of the k-th user to the received signal can be written as:

$$\mathbf{x}_k[m] = \begin{bmatrix} \mathbf{a}_{2k-1} & \mathbf{a}_{2k} \end{bmatrix} \begin{bmatrix} h_k & 0 \\ 0 & h_k \end{bmatrix} \begin{bmatrix} z_{2k-1}(m) \\ z_{2k}(m) \end{bmatrix}, \tag{3.10}$$

where $z_{2k-1}(m) = [b_k(m) + b_k(m-1)]/2$ and $z_{2k-1}(m) = [b_k(m) - b_k(m-1)]/2$. The vectors $\mathbf{a}_{2k-1}$ and $\mathbf{a}_{2k}$ of size $(QN_c \times 1)$ are the k-th user propagation delay and code waveforms given by:

$$\mathbf{a}_{2k-1} = [d_k \mathbf{D}(p_k + 1, 1) + (1 - d_k)\mathbf{D}(p_k, 1)]\, \mathbf{c}_k \tag{3.11}$$
$$\mathbf{a}_{2k} = [d_k \mathbf{D}(p_k + 1, -1) + (1 - d_k)\mathbf{D}(p_k, -1)]\, \mathbf{c}_k, \tag{3.12}$$

where p_k and d_k are the integer and the fractional part of the propagation delay respectively, with respect to the chip period T_c. The permutation matrix $\mathbf{D}(r, \alpha)$ of size

$(QN_c \times QN_c)$ is defined as:

$$\mathbf{D}(r,\alpha) = \begin{bmatrix} \mathbf{0} & \mathbf{I}_{QN_c - r} \\ \alpha \mathbf{I}_r & \mathbf{0} \end{bmatrix}. \tag{3.13}$$

The codeword $\mathbf{c}_k$ has dimension $(QN_c \times 1)$ and is defined as:

$$\mathbf{c}_k = [c_k(QN_c)\ c_k(QN_c - 1) \ldots c_k(1)]^T. \tag{3.14}$$

We can therefore write the system model as:

$$\mathbf{x}[m] = \mathbf{A}[\tau]\mathbf{H}\mathbf{z}[m] + \mathbf{w}[m], \tag{3.15}$$

where $\mathbf{A}(\tau) = [\mathbf{a}_1 \ldots \mathbf{a}_{2K}]$ of size $(QN_c \times 2K)$, $\mathbf{H} = \mathrm{diag}(h_1, h_1, \ldots, h_K, h_K)$ is a diagonal matrix of size $(2K \times 2K)$, $\mathbf{z}[m] = [z_1(m), z_2(m), \ldots, z_{2K}(m)]^T$ of size $(2K \times 1)$. The vector $\tau = [\tau_1, \ldots, \tau_K]^T$ contains all the users' propagation delay. The system model described in (3.15) is derived based on the assumption that the spreading codes and data bits are binary antipodal.

3.2.1 Propagation delay estimation

Three main approaches to delay estimation in short-code DS-CDMA systems are presented in this section: correlation based methods, subspace methods and maximum likelihood methods. Other methods such as MMSE estimator and space-time delay estimators are also mentioned.

Correlation based methods

The traditional approach to propagation delay estimation is the sliding correlator [129]. The sliding correlator is derived and works well in the case of a single user in additive white Gaussian noise (AWGN). Its performance is severely limited in multi-user scenarios and it is very sensitive to near-far effects. Assuming that $b_k(m) = 1$ for a time period M, the correlator estimate of the delay τ_k is given by:

$$\hat{\tau}_k = \arg \min_{\tau \in [0,T)} \left[-\sum_{m=1}^{M} \frac{|\mathbf{a}_{2k-1}^H(\tau)\mathbf{x}[m]|^2}{\|\mathbf{a}_{2k-1}(\tau)\|^2} \right]. \tag{3.16}$$

It can be observed that the sliding correlator needs extra side information (only $'1'$ bits transmitted) to perform the delay estimation. The sliding correlator performance can be significantly improved if the received vector is whitened with the matrix $\mathbf{R}^{-1/2}$, where $\mathbf{R} = E\{\mathbf{x}[m]\mathbf{x}^H[m]\}$ is the received sequence covariance matrix [199].

Subspace based methods

A new class of subspace based algorithms for propagation delay estimation has been introduced in [160] and [161]. Initially the algorithm was proposed in [161] for stationary flat frequency channels and further extended in [160] for frequency selective fading channels.

By assuming that the channels are unknown and time-invariant and the propagation delays are unknown and are deterministic parameters, the received sequence covariance matrix can be written as:

$$\begin{aligned} \mathbf{R} &= E\{\mathbf{x}[m]\mathbf{x}^H[m]\} = \mathbf{A}\mathbf{H}E\{\mathbf{z}[m]\mathbf{z}^H[m]\}\mathbf{H}^H\mathbf{A}^H + \sigma^2\mathbf{I}_{QN_c} \\ &= \mathbf{A}\mathbf{S}\mathbf{A}^H + \sigma^2\mathbf{I}_{QN_c}, \end{aligned} \tag{3.17}$$

where $\mathbf{S} = \mathbf{H}E\{\mathbf{z}[m]\mathbf{z}^H[m]\}\mathbf{H}^H$ of size $(2K \times 2K)$, $\mathbf{A}$ and $\mathbf{H}$ are as in (3.15), and σ^2 is the additive noise variance. The matrix $\mathbf{A}$ is assumed to have full rank. Since $\mathbf{ASA}^H$ is symmetric and has the rank $2K$, its eigenvalue decomposition can be expressed as follows:

$$\mathbf{ASA}^H = [\mathbf{E}_s \;\; \mathbf{E}_n] \begin{bmatrix} \mathbf{\Lambda} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{bmatrix} [\mathbf{E}_s \;\; \mathbf{E}_n]^H, \tag{3.18}$$

where $\mathbf{E}_s$ of size $(QN_c \times 2K)$ and $\mathbf{E}_n$ of size $(QN_c \times (QN_c - 2K))$ include the basis vectors of the orthogonal signal and noise subspaces, respectively. The foundation of the subspace based delay estimators is the observation that the columns of $\mathbf{A}$ and $\mathbf{E}_s$ span the same subspace, for the true value of the delay τ. Consequently, the columns of $\mathbf{E}_n$ span the orthogonal noise subspace. This means that the columns $\{\mathbf{a}_1, \ldots, \mathbf{a}_{2K}\}$ of $\mathbf{A}$ are orthogonal to any vector in the noise subspace. The noise subspace is defined in terms of the eigenvalues of the output covariance matrix $\mathbf{R}$. In practice this matrix is unknown and is usually estimated using the sample covariance matrix:

$$\hat{\mathbf{R}} = \frac{1}{M} \sum_{m=1}^{M} \mathbf{x}[m]\mathbf{x}^H[m]. \tag{3.19}$$

The estimated noise subspace $\hat{\mathbf{E}}_n$ is defined by the eigenvectors corresponding to the smallest $QN_c - 2K$ eigenvalues of $\hat{\mathbf{R}}$.

The original MUltiple Signal Classification (MUSIC) [149] algorithm is formulated for the case where each column of $\mathbf{A}$ is parameterized by a distinct parameter. This is not the case here since each user is characterized by two delay vectors $\mathbf{a}_{2k-1}(\tau_k)$ and $\mathbf{a}_{2k}(\tau_k)$. A modified version of MUSIC is used instead to estimate τ_k:

$$\hat{\tau_k} = \arg \min_{\tau \in [0, N_c)} \left(\frac{\left\| \hat{\mathbf{E}}_n^H \mathbf{a}_{2k-1}(\tau) \right\|^2}{\left\| \mathbf{a}_{2k-1}(\tau) \right\|^2} + \frac{\left\| \hat{\mathbf{E}}_n^H \mathbf{a}_{2k}(\tau) \right\|^2}{\left\| \mathbf{a}_{2k}(\tau) \right\|^2} \right). \tag{3.20}$$

In the case of perfect subspace estimation it can be observed that $\hat{\tau_k} = \tau_k$. The extension to multipath fading channels [160] is straight-forward. It includes the channel gains in the transmitted signal vector, therefore the delay matrix $\mathbf{A}$ is still constant and deterministic. Theoretical Cramer-Rao lower bounds (CRLB) are derived for the delay estimators in both single path and multipath approaches. The CRLB indicates that the variance of the delay estimation error of a specific user is independent on the parameters of the other users. This suggest algorithm robustness in the face of the near-far effect.

Östman et al. proposed in [120] an improvement of the MUSIC based delay estimator. The basic idea is to compute the output sequence covariance matrix by extending the observation interval to span more than one symbol duration. The simulation and analytical results show an improved performance over the originally proposed subspace delay estimator.

One drawback of the subspace methods is block-oriented processing, i.e. the delays are estimated after M signal blocks have been processed. Parkvall proposed in [124] a method for recursive estimation of the output covariance matrix. The delays are estimated using a signal subspace method instead of the noise subspace method of (3.20). The performance of the recursive method is comparable to that of the block processing approach, especially for a small number of active users. In [139] the MUSIC algorithm is considered in a non-stationary environment. Several subspace tracking methods for the noise sub-space are studied in conjunction with the delay estimator. The best results are provided by the algorithm from [202].

A different approach to the subspace based delay estimation problem is proposed in [144]. The Estimation of Signal Parameters via Rotation Invariant Technique (ESPRIT) algorithm [143] based on the shift-invariance property is used to estimate the propagation delays in a closed-form solution. Starting from (3.17), it is assumed that $\mathbf{C}$ is a non-singular matrix defined as $\mathbf{C}^{-1} = \mathbf{S}^H\mathbf{A}$. Two matrices $\mathbf{A}_1$ and $\mathbf{A}_2$ are formed from the first $P < 2K$ and the last P columns of $\mathbf{A}$ respectively, and all the $'0'$ columns in the rest. Consequently, the matrices $\mathbf{S}_1$ and $\mathbf{S}_2$ are formed from the columns of $\mathbf{S}$. With these definitions it is shown that:

$$\mathbf{S}_2 = \mathbf{S}_1\mathbf{\Psi}, \tag{3.21}$$

where $\mathbf{\Psi}$ is a matrix with the property that its eigenvalues contain information of the propagation delays. In a realistic scenario the statistics have to be estimated and the matrix $\mathbf{\Psi}$ is given by:

$$\hat{\mathbf{\Psi}} = \left(\hat{\mathbf{S}}_1^H\hat{\mathbf{S}}_1\right)^{-1}\hat{\mathbf{S}}_1^H\hat{\mathbf{S}}_2 \tag{3.22}$$

The ESPRIT algorithm gives consistent estimates of the delays τ_k from the eigenvalues of $\hat{\mathbf{\Psi}}$. A similar approach to the delay estimation problem is proposed in [128], where an ESPRIT delay estimator in frequency domain is proposed. The propagation delays are contained in the frequencies of complex exponentials in the frequency domain. The algorithm finds the common column span among the complex exponential matrices corresponding to the K users. The ESPRIT algorithm is applied on the resulting shift-invariant subspace in order to estimate the propagation delays.

Maximum likelihood methods

A maximum likelihood (ML) method for delay estimation is proposed in [161]. It is shown that the optimization problem is separable with respect to noise variance, therefore the ML estimates of the channels, propagation delay and transmitted data are given by:

$$\begin{bmatrix} \hat{\mathbf{h}} \\ \hat{\tau} \\ \hat{\mathbf{z}}[m] \end{bmatrix} = \arg\min_{\mathbf{h},\tau,\mathbf{z}} \sum_{m=1}^{M} \|\mathbf{x}[m] - \mathbf{A}\mathbf{H}\mathbf{z}[m]\|^2 . \tag{3.23}$$

This estimator has the major disadvantage that all the possible combinations of the transmitted symbols $\mathbf{z}[m]$ have to be tested in order to obtain a true ML estimate of the unknown parameters. An approximate ML (AML) scheme for the estimation of the delays only is proposed in order to overcome this problem:

$$\hat{\tau}^{AML} = \arg\min_{\tau} \operatorname{trace}\left[(\mathbf{I} - \mathbf{A}\mathbf{A}^{\#})\hat{\mathbf{R}}\right], \tag{3.24}$$

where $(.)^{\#}$ denotes the pseudo-inverse operator and $\hat{\mathbf{R}}$ is the sample covariance matrix of the output $\mathbf{x}[m]$. The AML scheme is studied in simulations and gives results very close to those of the subspace MUSIC method. The AML method has much lower computational complexity than the ML. Similarly to the MUSIC estimator, AML estimator does not achieve the CRLB, even for high SNR. The AML cost function is highly nonlinear with many local minima and it is sensitive to correct initialization.

The ML schemes presented before estimate all the users' delays simultaneously. Zheng et al. propose in [209] an ML estimator for the propagation delays of a single user in frequency flat channels. This timing ML estimator models the known training sequence of the user of interest as the desired signal. The other users' signals and the thermal noise are modeled as colored Gaussian noise uncorrelated with the desired signal. The colored noise covariance matrix can be estimated as:

$$\hat{\mathbf{Q}} = \frac{1}{M}\sum_{m=1}^{M}[\mathbf{x}[m] - \hat{\mathbf{D}}\mathbf{z}[m]][\mathbf{x}[m] - \hat{\mathbf{D}}\mathbf{z}[m]^H], \tag{3.25}$$

where $\hat{\mathbf{D}} = \hat{\mathbf{R}}_{zx}^H\hat{\mathbf{R}}_{zz}^{-1}$, $\hat{\mathbf{R}}_{zx}$ is the input-output sample correlation matrix and $\hat{\mathbf{R}}_{zz}$ is the input sequence sample covariance matrix. Giving a sufficiently large training sequence for estimating the statistics, the ML estimate of the propagation delay τ_0 is given by [209]:

$$\begin{aligned}
&\hat{\tau_0} = \arg\max_{\tau_0}\left\{\frac{|\tilde{\mathbf{a}}_1^H(\tau_0)\tilde{\mathbf{d}}_1 + \tilde{\mathbf{a}}_2^H(\tau_0)\tilde{\mathbf{d}}_2|^2}{\|\tilde{\mathbf{a}}_1(\tau_0)\|^2 + \|\tilde{\mathbf{a}}_2(\tau_0)\|^2}\right\}, &(3.26)\\
&\tilde{\mathbf{a}}_1(\tau_0) = \hat{\mathbf{Q}}^{-1/2}\mathbf{a}_1(\tau_0), \quad \tilde{\mathbf{a}}_2(\tau_0) = \hat{\mathbf{Q}}^{-1/2}\mathbf{a}_2(\tau_0),\\
&\tilde{\mathbf{d}}_1 = \hat{\mathbf{Q}}^{-1/2}\hat{\mathbf{d}}_1, \quad \tilde{\mathbf{d}}_2 = \hat{\mathbf{Q}}^{-1/2}\hat{\mathbf{d}}_2,
\end{aligned}$$

where $\mathbf{a}_i(\tau_0)$ respectively $\hat{\mathbf{d}}_i$ is the i-th column of $\mathbf{A}(\tau_0)$ and $\hat{\mathbf{D}}$ respectively. Under the assumption that the interference plus noise is Gaussian distributed, the ML estimator exhibits desirable large-sample properties. It is asymptotically efficient as the length of the training sequence goes to infinity. The main drawback of the large sample ML (LSML) delay estimator is that it may only be applied to time invariant channels. The simulation results in these environments show that the LSML estimator clearly outperforms the sliding correlator. In heavily loaded cells it also outperforms the subspace based estimators. For a large number of training symbols and with sufficiently high signal power it achieves the performance bound given by the CRLB.

Bensley and Aazhang also proposed a ML estimator for the propagation delay of a single user in MUI and additive noise [10]. The mean sequence of the received samples $\mathbf{x}[m]$ is computed recursively and it is shown to converge to a complex Gaussian sequence. The ML estimate of the delay is found by:

$$\hat{\tau_0} = \arg\max_{\tau}\frac{|\hat{\mathbf{m}}_i^H\hat{\mathbf{K}}_i^{-1}\mathbf{a}_0(\tau)|^2}{\mathbf{a}_0^H(\tau)\hat{\mathbf{K}}_i^{-1}\mathbf{a}_0(\tau)}, \tag{3.27}$$

where $\hat{\mathbf{m}}_i$ is the current sample mean of the received sequence and $\hat{\mathbf{K}}_i$ is the current covariance matrix estimate. A computationally efficient method for updating the estimates is also proposed. In [42] it is proved that under the condition of a fixed preamble of the transmission bits for each user, the ML delay estimators of [209] and [10] are equivalent. A more efficient alternative to LSML is proposed in [85], where a decoupled multi-user code-timing acquisition (DEMA) method is proposed. The algorithm is based on the system model in (3.15), written as:

$$\mathbf{x}[m] = [h_1\mathbf{A}_1(\tau_1), \ldots, h_K\mathbf{A}_K(\tau_K)]\,\mathbf{z}[m] = \mathbf{B}\mathbf{z}[m]. \tag{3.28}$$

The transmitted bits are assumed independent and identically distributed (i.i.d). Therefore the input covariance matrix is $\mathbf{R}_{zz} = \mathbf{I}_{2K}$. The matrix $\mathbf{B}$ is estimated by:

$$\hat{\mathbf{B}} = \hat{\mathbf{R}}_{zx}^H\hat{\mathbf{R}}_{zz}^{-1}, \tag{3.29}$$

where $\hat{\mathbf{R}}_{zx}$ and $\hat{\mathbf{R}}_{zz}$ are the sample input-output and input covariance matrices respectively. The estimates of the propagation delay and channel for the k-th user are given by:

$$\hat{\tau}_k = \arg\max_{\tau_k} \frac{|\mathbf{a}_k^H(\tau_k)\hat{\mathbf{b}}_k|^2}{\mathbf{a}_k^H(\tau_k)\mathbf{a}_k(\tau_k)} \tag{3.30}$$

$$\hat{h}_k = \frac{\mathbf{a}_k^H(\hat{\tau}_k)\hat{\mathbf{b}}_k}{\mathbf{a}_k^H(\hat{\tau}_k)\mathbf{a}_k(\hat{\tau}_k)} \tag{3.31}$$

where the vectors $\mathbf{a}_k$ and $\hat{\mathbf{b}}_k$ are obtained by stacking into the column vector the elements of $\mathbf{A}_k(\tau_k)$ and $\hat{\mathbf{B}}_k$ respectively. Therefore, the problem of estimating the K pairs of parameters is decoupled in K smaller problems of estimating 2 parameters. An efficient method for minimizing the cost function in (3.30) is also proposed, and is similar to that in [209]. In the noiseless case, the exact parameters are obtained with a finite number of available training bits. The simulation results show that DEMA outperforms LSML in heavy loaded cells.

Other methods for delay estimation

A MMSE delay estimation method is proposed in [158, 159]. A near-far resistant single-user detector $\mathbf{w}_{mmse}$ is chosen for the desired user to minimize the mean squared error:

$$\mathcal{J} = E\left[|b_0(m) - \mathbf{w}_{mmse}^H \mathbf{x}[m]|\right], \tag{3.32}$$

where $b_0(m)$ are the transmitted data of the user of interest. In practice the receiver vector $\mathbf{w}_{mmse}$ is computed using an adaptive filtering technique such as least mean squares (LMS) or recursive least squares (RLS). Once the receiver vector is computed, the time delay can be estimated using a correlator-type approach:

$$\hat{\tau}_0 = \arg\max_{\tau_0} \left\{ \frac{||\mathbf{a}_1^H(\tau_0)\mathbf{w}_{mmse}||^2}{||\mathbf{a}_1(\tau_0)||^2} \right\}. \tag{3.33}$$

In [209] the performance of the MMSE delay estimator is shown to be more robust to near-far effects and cell load than the sliding correlator. However, it is more sensitive than the subspace estimators.

The delay estimator performance may be improved if an antenna array is available at the receiver. It is possible to take advantage of the benefits of the antenna arrays such as SNR gain and diversity gain. In [152], the general mathematical framework is presented for the problem of using antenna arrays for synchronization. In this context, ML and subspace ESPRIT delay estimators are investigated. Space-time ML delay estimators are also proposed in [151] and [96]. All these techniques consider the problem of synchronizing a single user of interest while the interference and noise are modelled as zero-mean circularly complex Gaussian with unknown statistics. These statistics are usually estimated using training data for all users. The spatial diversity achieved via antenna array provides an additional dimension in which to separate the desired user signal from the noise and interference.

Discussion

The delay estimators have to be able to deliver a desired level of performance in realistic scenarios. They have to be robust in face of different impairments of the DS-CDMA networks such as power imbalances and interference.

The subspace delay estimators are blind methods in the sense that they do not need knowledge of the users' transmitted symbols. The sliding correlator, ML and MMSE methods need a significant amount of training data in order to estimate the input-output statistics. From this perspective the subspace methods are more attractive solutions.

The correlation based algorithms are very sensitive to interference and near-far effects. The subspace and ML methods deliver a very robust performance in near-far scenarios. The theoretical results show that the performance bounds of the subspace and ML estimators for a certain user is independent on the parameters of the other users. The ML estimators in general, and the algorithm of [85] in particular, offer better performance in heavy loaded cells than the other methods. Subspace methods are limited to scenarios with a lower number of active users in order to fulfill the low rank signal assumptions. In low SNR scenarios subspace methods may not perform well since the subspaces are not well separated.

The ML, MMSE and sliding correlator are generally derived for frequency flat channels whereas the subspace methods [160] can be applied in frequency-selective fading channels.

The algorithms complexity play an important role in practical systems. The ML estimators achieve the performance bounds given by the CRLB at the cost of higher computational complexity. The subspace and approximate ML methods do not achieve the CRLB even in high SNR scenarios. However, they have much lower computational complexity and offer a good complexity-performance trade-off.

The subspace methods are derived based on the assumption of white Gaussian noise and perform worse in colored and heavy tailed noise scenarios. Non-parametric statistics can be used for the estimation of the subspaces [186] in order to overcome the problem of heavy tailed noise. The colored noise problem can be solved by estimating the covariance matrix $\mathbf{R}$ of noise plus interference and then using $\mathbf{R}^{-1/2}$ for whitening. Another solution for the colored noise case is proposed in [99]. In a dual antenna scenario, and assuming that the noise between the antenna elements is uncorrelated, the generalized correlation decomposition (GCD) [197] can be used to estimate the noise subspace.

The subspace methods may be of practical interest since many of their impairments can be mitigated in realistic scenarios. They offer a good performance at acceptable computational cost. Moreover, they can be applied in scenarios with frequency and time selective channels unlike the other methods presented in this subsection.

The most important delay estimation methods for short-code DS-CDMA are summarized in Table 3.1 according to several classification criteria.

3.2.2 Receiver algorithms

In this section different receiver algorithm strategies for short-code DS-CDMA are reviewed. The standard RAKE receiver [131] is discussed first. Multiuser detectors (MUD) [182] providing improved robustness with regard to near-far effects in comparison to a RAKE receiver are presented . The original MUD [182] suffers from a high degree of computational complexity, therefore more efficient computational schemes based on interference cancellation (IC) [180, 187] are introduced. Different linear receiver strategies, including weighted LS and linear MMSE detectors [119] are also presented as well as subspace based channel estimators [9]. Finally blind receiver techniques are discussed as a spectral efficient alternative to the methods using training sequences.

	Sliding correlator [129]	**Subspace** [160, 161, 144]	**ML** [10, 161, 209, 85]	**MMSE** [158, 159]
Training data	Data-aided	Blind	Data-aided	Data-aided
Performance	Sensitive to near-far ratio (NFR) and large cell load	Resistant to high NFR but sensitive to large cell load	Resistant to high NFR and large cell load	Sensitive to high NFR and large cell load, more robust than sliding correlator
Complexity	Low	More complex than the sliding correlator	More complex than subspace methods	Lower complexity than ML and subspace methods, higher than sliding correlator
Channels cond.	Freq. flat fading	Freq. selective fading	Freq. flat time invariant	Freq. flat time invariant

Table 3.1: The classification of the delay estimators for short-code DS-CDMA

The RAKE receiver

The standard receiver in DS-CDMA is the RAKE receiver proposed initially in [131]. A thorough description of the RAKE receiver can be found in [132, 188]. In the RAKE receiver multipath diversity is utilized by correlating the received signal with spreading codes that are synchronized to different multipaths in different RAKE fingers. The finger outputs are combined in order to obtain maximum SNR at the receiver output before data detection. An excellent overview of different combining strategies can be found in [76]. The RAKE receiver is optimal in the single-user case and assumes that the users' spreading codes are orthogonal. In asynchronous transmission this receiver is more vulnerable to the interference from the other users. This is due to the fact that it is not possible to design spreading sequences that are orthogonal for all the time offsets [132]. Consequently, interference from the other users is unavoidable in an asynchronous transmission when the single-user detector is employed at the receiver. In this type of scenario, the near-far problem is particularly serious. The performance of the RAKE receiver is highly degraded when the near-far effect exists [129]. The near-far problem may be compensated for by using strict power control schemes. In wireless communications this is a very difficult task since the received powers often vary drastically. Another way of handling the near-far problem is to use near-far resistant receivers without strict power control.

Multiuser detectors

Unlike the RAKE receiver, the MUD accounts for the presence of the interference in the channel and therefore overcome the problems of the conventional receiver. Assuming AWGN channels, Verdu proposed in [182] the optimum ML MUD. The algorithm is optimal in the sense that it uses the whole received waveform to produce sufficient statistics for any symbol decision. The complexity of the MUD increases exponentially with the number of users and makes it impractical. The decorrelating receiver proposed by Lupas and Verdu in [98] constitutes a suboptimal scheme of the optimum MUD. It has a much lower computational complexity since it may be implemented by a K input K output linear-time-invariant filter, whereas the optimum MUD is implemented using a high complexity Viterbi algorithm. The decorrelating detector complexity is further reduced in [20], by shortening the number of coefficients in the filter. A MMSE linear MUD is proposed in [100]. Even the suboptimal MUD are considerably complex, especially in asynchronous systems. These methods assume prior knowledge of the channels, propagation delays and users spreading codes.

Interference cancellation techniques

The IC methods fall in the category of MUD also, even though we treat them separately. They use a slightly different approach than the methods presented in the previous subsection. The contributions of the interfering users is subtracted from the decision signal of the desired user prior to data detection.

Viterbi in [187] proposed the successive interference cancellation (SIC) receiver. The idea is to first decode the user with the highest strength and then subtract its contribution from the received signal. Then the operation is repeated successively for the remaining users, in decreasing order of their powers. Therefore the users' power has to be known a priori. Patel and Holtzman in [126] proposed an improved SIC scheme where the users are ranked based on the output of their correlation with the spreading codes. Unlike the original method [187], where the bit decisions are fed back in order to cancel the interference, the chip sequences are fed back in the modified SIC.

The SIC receivers often assume perfect knowledge of the channel impulse responses and propagation delays. A single-path channel is also commonly assumed. In [101] a multi-stage SIC detector is proposed in multipath channels. A modified RAKE combiner is used instead of the correlator to rank the users. Thus the receiver takes advantage of the frequency-diversity of the channels. The method is shown to achieve a significant improvement in performance over the traditional SIC detector at the cost of increased complexity. Delay error resistant SIC detectors are proposed in [49, 198, 206], where delay tracking loops are included in the SIC detector. In [198] a global fixed timing error identical for all users is assumed. The performance is evaluated under ideal perfect power control. In [206] the timing errors differ among the users and the performance is studied in severe near-far conditions. Unlike in [49], the transmitted data is unknown. Therefore, the data detection and delay tracking are performed jointly. The method is implemented using a sliding window technique in order to track user delays. The delay error estimate of the current window is used to update the time delay information used in the next window. The delay error-robust SIC detectors assume an initial acquisition of the propagation delays.

A different approach to the interference cancellation, the multi-stage parallel interference cancellation (PIC), was proposed by Varanasi and Aazhang in [180]. The difference from the SIC is that at each stage all the users are detected and these decisions are used in the next stage to reduce the MUI. A significant improvement to PIC is achieved in [31] where a weighted cancellation scheme is proposed. The current decision statistics are the weighted sum of the previous statistics and the statistics resulting from the interference cancellation based on the tentative decisions.

Assuming that the system is symbol synchronous, it is proved in [51, 137] that the linear weighted PIC corresponds to the linear matrix filtering that can be performed directly on the received chip-matched filtered signal vector. In [137] the necessary conditions in the eigenvalues of the code correlation matrix and weighting factors required to ensure convergence are derived. By choosing proper weighting, the weighted PIC needs exact K stages to implement the exact steepest descent MMSE detector [51]. These properties hold true for single-path channels.

The performance of SIC and PIC is compared in [126] for asynchronous transmissions but with known channels and propagation delays. Both IC schemes outperform the conventional RAKE receiver even when perfect power control is assumed. In this case PIC also outperforms SIC. However, in fading channels with near-far effect SIC provide a better performance than PIC. A quick overview of the structure of the algorithms leads to the conclusion that the SIC scheme is simpler and possibly easier to implement with a minimal increase in receiver hardware from the conventional receiver. PIC usually delivers good performance with a lower decision delay than SIC due to its parallel processing ability. Most of the IC schemes assume perfect channel and delay information. These methods are also easy to accommodate in long-code systems.

Subspace methods

Bensley and Aazhang [9] consider delay and CIR estimation using subspace decomposition for single path and multi-path channels. In the single path channel case, a probabilistic approach leads to an ML solution to the delay estimation. The method is based on the observation that the projections of the estimated noise subspace eigenvectors onto the estimated signal subspace are jointly Gaussian with a zero mean and covariance matrix $\mathbf{Q}$. The covariance matrix can be computed from the signal subspace parameters and additive noise variance. Defining the vector $\mathbf{a}_k(\tau_k) = \mathbf{a}_{2k-1}(\tau_k) + \mathbf{a}_{2k}(\tau_k)$, the ML estimate of the propagation delay is given by:

$$\hat{\tau}_k = \arg\min_{\tau_k} \mathcal{J}(\tau_k) \tag{3.34}$$

$$\begin{aligned}\mathcal{J}(\tau_k) = & -(N_c - 2K)\ln\left(\mathbf{a}_k^H(\tau_k)\mathbf{Q}\mathbf{a}_k(\tau_k)\right) - \\ & -J\frac{\mathbf{a}_k^H(\tau_k)\hat{\mathbf{E}}_n\hat{\mathbf{E}}_n^H\mathbf{a}_k(\tau_k)}{\mathbf{a}_k^H(\tau_k)\mathbf{Q}\mathbf{a}_k(\tau_k)},\end{aligned} \tag{3.35}$$

where J is the interval over which the output covariance matrix is estimated. The obtained solution is similar to that in [161] if only the numerator is maximized and the denominator is ignored, i.e. $\mathbf{a}_k^H(\tau_k)\mathbf{Q}\mathbf{a}_k(\tau_k)$ is constrained to be equal to 1. For the multipath channels, the CIRs are estimated using a geometric approach. The delay vectors $\mathbf{a}_{2k-1}(\tau_k)$ and $\mathbf{a}_{2k}(\tau_k)$ contain the channel attenuations also. The objective is to minimize the l_2 norm of the projections of the signal vectors onto the noise subspace:

$$\hat{\mathbf{h}}_k = \arg\min_{\mathbf{h}\in\mathcal{H}}\left[\left\|\mathbf{a}_{2k-1}^H(\tau_k)\hat{\mathbf{E}}_n\right\|^2 + \left\|\mathbf{a}_{2k}^H(\tau_k)\hat{\mathbf{E}}_n\right\|^2\right], \tag{3.36}$$

where $\mathcal{H}$ is the set of feasible impulse responses, determined by an a priori channel model. The minimization problem reduces to an eigenvalue problem solution.

Parkvall et al. [125] propose several structures for receivers for data demodulation without a priori knowledge of the propagation delays. Single-path channels are assumed. The receiver performs the subspace delay estimation [161] as an initial step. Then the receiver demodulates the data corresponding to the desired user k by projecting the received M data vector onto a space spanned by the columns of the matrix $\mathbf{W} = [\mathbf{w}_1 \ \mathbf{w}_2]$ of size $QN_c \times 2$:

$$\mathbf{r}[m] = \mathbf{W}^H \mathbf{x}[m] = h_1 \mathbf{W}^H [\mathbf{a}_1 \ \mathbf{a}_2] \begin{bmatrix} z_1(m) \\ z_2(m) \end{bmatrix} + \tilde{\mathbf{n}}[m], \tag{3.37}$$

where $\tilde{\mathbf{n}}[m]$ is the projection of noise plus interference onto the space spanned by the columns of $\mathbf{W}$. The projected noise and interference are usually non-white, but the whiteness assumption does not have significant influence on the performance. The matrix $\mathbf{W}$ is found by using either the decorrelation criterion or the MMSE criterion. The decorrelation criterion tries to eliminate the MAI by projecting it onto a plane that is orthogonal to all interfering users. This solution is achieved using a Gram-Schmidt orthogonalization on the delay matrix $\mathbf{A}$. Therefore, the signatures of the interfering users are needed. The MMSE criterion minimizes the expected value of the squared error between the transmitted and detected symbols. The solution is given by solving the Wiener-Hopf equation and using the orthogonality property between the noise and signal subspaces. Each projected vector $\mathbf{r}[m]$ has contributions from 2 transmitted symbols. This problem is similar to ISI and therefore the authors propose two approaches to data demodulation: a decision feedback technique and a MLSE implemented using the Viterbi algorithm [132].

Blind methods

The blind multiuser detectors offer improved effective data rates by not requiring training signals. They are usually derived for short-code CDMA systems, due to signal cyclostationarity. The synchronization of the users is generally assumed, as is knowledge of the users' spreading codes. This area of research has been a very active one in recent years [61, 166, 190, 191, 192, 193]. The basic idea in many of the blind receivers in CDMA is that the system can be formulated as a symbol rate MIMO system. They have different user signals as the inputs and the chip-rate sampled data per symbol as the N_c outputs, where N_c is the spreading factor. Therefore, in principle, existing approaches to blind MIMO channel identification and deconvolution can be applied to the current problem [97, 165]. Blind multiuser detection is therefore subject to well known blind identification problems and especially to identification ambiguities. In a MIMO system this usually translates to matrix ambiguities, meaning that the MIMO channel matrix is identified up to a unitary ambiguity matrix. This problem is critical and is very difficult to solve [185].

Many of the proposed blind methods are based on the linear MMSE multiuser receiver [61, 100]. The earlier method uses the minimum output energy (MOE) detector steaming from [184] with constrained surplus energy optimization. The blind channel estimation method proposed in [111] is applied in CDMA in various algorithms [93, 166]. Subspace methods have been used in numerous studies for blind multiuser detection [190, 191, 192, 193]. The main drawback of the subspace based blind MUD is that they are applicable for underloaded systems when a low rank signal model holds.

A code-aided CMA blind MUD was proposed in [172]. A linear equalizer is designed to minimize the CMA cost function of the equalizer output with respect to the equalizer coefficients. Constrained CMA leads to the extraction of the desired user's signal, whereas unconstrained CMA leads to extraction of any one of the active users. Unlike the majority of the blind MUD methods, this algorithm does not require a priori synchronization with the desired user's signal.

A blind CDMA receiver is proposed by Tsatsanis and Xu in [171], stemming from the minimum variance distortionless response (MVDR) beamforming algorithm extensively studied in array processing [179]. The receiver design problem is in determining for each user of interest a receive filter which provides the desired signal. The filter can be optimized by minimizing the output variance subject to the constraint that the response of the user of interest is constant. Several adaptive techniques for solving blindly the constraint optimization problem are proposed in [201]. Therefore, the computational expensive matrix inversion of [171] is avoided. The proposed blind receivers outperform the subspace blind methods, especially in heavy loaded cells.

There are many other blind receivers for short-code DS-CDMA proposed in the literature [172, 173]. Blind receivers for DS-CDMA are outside the scope of this thesis, they are mentioned simply to give the reader a complete overview of DS-CDMA receiver algorithms. A good review of existing blind methods in DS-CDMA can be found in [62, 106].

Other methods

Relying on the property that correlated time-domain data sequences are asymptotically uncorrelated in the frequency domain, Tang and Bar-Ness [162] propose a frequency domain delay and CIR estimation method. The channels are assumed to be frequency non-selective, therefore the CIR of the desired user can be estimated from the frequency domain data using a ML scheme. After the parameter estimation, the adaptive MOE detection method of [61] is applied to the asynchronous system for data detection.

In [119] several near-far resistant detection methods for AWGN channels are investigated. Assuming knowledge of the delays, the conventional matched filter is compared to LS, weighted LS and MMSE detectors. As expected, the matched filter receiver is clearly outperformed by the other detectors. The weighted LS detector is the most robust in the face of near-far effects.

Concluding remarks

Conventional RAKE receiver performance is severely limited by the interference and near-far effects. More robust techniques are needed for a reliable performance. The MUD and IC methods offer a better alternative when coping with the impairment specific to DS-CDMA networks. The MUD have a high computational complexity and and are usually derived for flat frequency channels. Moreover, the interference suppression provided by the MUD may come at the expense of noise enhancement [98]. This is an undesirable behavior which results in a significant performance degradation even at high SNR. Therefore, conventional MUD are only of theoretical interest.

The interference cancellation methods, both SIC and PIC, have a much lower complexity than the other MUDs. The PIC structure in particular allows for efficient practical implementation using parallel processing. The IC are flexible techniques able to accommodate to both short-code and long-code CDMA. The main drawback of the IC methods is the requirement for prior synchronization, at least at symbol level. The channels are also usually assumed known. Therefore, prior synchronization and channel estimation stages are necessary.

The subspace delay estimation mentioned in Section 3.2.1, can be used as the first stage of the DS-CDMA receiver. Then, linear MMSE or decorrelation receivers may be employed, as in [119, 125]. This approach is more practical, it also contains the users' synchronization stage. The performance achieved is good in underloaded cells scenarios and in a high SNR regime. Decorrelation receiver may enhance the noise levels and therefore the linear MMSE receivers are preferable. Subspace channel estimator in [9] may offer an alternative solution but its performance depends on the prior knowledge of the channel model. However, there is an extensive research work regarding the channel modeling in mobile communications.

Known reference signals are often required by the DS-CDMA receivers. Blind receivers improve the effective data rates, but they often suffer from high computational complexity. This can be reduced by using adaptive techniques [201]. Many of the blind DS-CDMA receivers reduce to the problem of blind MIMO identification. In this case, the difficult problem of finding a unitary ambiguity matrix has to be solved and high computational complexity post-processing stages are needed.

The problems of synchronization, channel estimation and data detection in uplink DS-CDMA cannot be separately treated. They constitute different aspects of the same problem: a reliable receiver structure. The inevitable estimation errors in any stage of the receiver propagates in the following stages also. Unfortunately, in the literature there is little concern about these problems. Except [119, 125], most of the papers cited in this section consider the optimization of only one stage of the receiver.

A general classification of receiver strategies proposed for short-code DS-CDMA according to several criteria is presented in Table 3.2.

	RAKE [132, 188]	**MUD** [182, 98, 100]	**IC** [187, 180, 51]	**Subspace** [9, 125]	**Blind** [172, 171, 190, 191]
Side info	Channels and delays	Channels and delays	Channels and delays	Data-aided	No training data
Performance	Sensitive to NFR and large cell load	Resistant to high NFR and large cell load	Resistant to high NFR and large cell load	Resistant to high NFR and large cell load	Resistant to high NFR, sensitive to large cell load, remaining ambiguities
Complexity	Low	High	Higher than RAKE but lower than MUD	Lower than MUD but higher than IC	High
Channels cond.	Freq. selective fading	Freq. flat time invariant	Freq. selective fading	Freq. selective time invariant	Freq. selective time invariant

Table 3.2: The classification of the receiver algorithms for short-code DS-CDMA

3.3 Receiver structures for long-code DS-CDMA

The usage of long-codes in DS-CDMA brings various advantages, such as increased immunity to MUI and channel fading on the average. However, the long-codes destroy the cyclo-stationarity of the CDMA signals and cause the system to be time-varying. This situation makes many of the existing channel estimation and data detection approaches developed for short-code systems inapplicable. In uplink, the receiver algorithm performs the channel estimation and synchronization. Then, an equalization method is employed to reduce the ISI and MUI. Data decisions are made using the resulting equalized sequence.

Most of the commercial CDMA based communications systems (IS-95 [164] and proposed 3G [118]) use long-codes for spreading, with the period being much longer than the symbol period. Despite this, there has been limited research work carried out into long-code CDMA. In principle, many of the MUD schemes, including the optimum MUD [183] and the class of interference cancellation methods [126, 180] are applicable to long-code systems. However, implementation of the optimum MUD is far too complex and linear detectors suffer from the fact that the data estimation requires the inversion of time-varying matrices. In the next section, a review of the most important research trends and existing receiver algorithms for long-code CDMA systems are presented. A brief review of receiver algorithms for long-code CDMA, and especially blind receivers, can be found in [77, 106].

3.3.1 Propagation delay estimation

In this subsection the delay acquisition methods designed for long-code DS-CDMA are presented first. The traditional correlation based estimators are introduced, then ML as well as non-linear LS frequency domain approaches are presented. Tracking mode delay methods based on recursive estimators and delay locked loops are also introduced.

Traditional correlation based techniques, i.e. the sliding correlator, may be applied to long-code systems. An extensive and excellent review of the code acquisition methods based on correlation is presented in [74]. The main idea in these methods is to generate delayed replicas of the spreading code locally and correlate them with the received signal. The main correlation peak is at the time index equal to the propagation delay. As in the short-code systems, this technique suffers from two causes : interference and the near-far effect. Usually the central limit theorem is invoked to show that the MUI is Gaussian for a large number of users. This assumption does not necessarily hold for realistic scenarios where the number of users in the cell varies very quickly. Another problem is that the correlator detector is very sensitive to the near-far effect.

In the literature there are very few papers that deal with the delay acquisition for long-code systems. Delay tracking is an important approach in the delay estimation problem for long-code systems [92, 67, 68, 81, 110, 205]. This approach is called post-acquisition, and it deals with the tracking of the users' time-varying propagation delay after acquisition in a previous step.

Delay acquisition

An ML scheme for delay acquisition in flat fading channels is proposed in [104]. The synchronization of a new user accepted into the system is considered. The propagation delays of the interfering users and the spreading codes are assumed to be known. Assuming that M information symbols are transmitted, the discrete time $MN_c \times 1$ vector $\mathbf{y}_c$ containing the sampled output of the chip-matched filter of the received sequence with the spreading codes can be written as:

$$\mathbf{x}_c = h_1 \mathbf{u}_1(\tau_1) + \mathbf{U}\mathbf{h} + \mathbf{w}, \tag{3.38}$$

where h_1 is the channel gain of the user of interest, $\mathbf{u}_1(\tau_1)$ is the output vector of the chip-matched filter with the code of the user of interest, $\mathbf{U}$ is the matrix of the outputs of the chip-matched filters with the codes of the interfering users, $\mathbf{h}$ represents the channel attenuations of the interfering users and $\mathbf{w}$ is the additive noise vector.

Assuming that $\mathbf{x}_c$ and $\mathbf{U}$ are known, τ_1 is estimated. In order to reduce the computational complexity, the authors have assumed that only K_c out of K users are canceled out while the interference from the remaining $K - K_c$ users' signals is modeled as white Gaussian interference with known variance, and is included in the noise vector $\mathbf{w}$. The interference subspace is defined as the column space of $\mathbf{U}$. A projection matrix $\mathbf{P}$ onto the subspace orthogonal to the interference subspace, also called interference noise subspace, is found using a 'skinny' QR decomposition on $\mathbf{U}$:

$$\begin{aligned} \mathbf{U} &= \mathbf{Q}\mathbf{R} \\ \mathbf{P} &= \mathbf{I} - \mathbf{Q}\mathbf{Q}^H \end{aligned} \tag{3.39}$$

The projection of $\mathbf{x}_c$ onto the interference noise subspace is shown to be sufficient statistics for the estimation of the delay τ_1. Therefore, the ML delay estimator is given by [104]:

$$\hat{\tau_1} = \arg\max_{\tau} \frac{\Re\{\mathbf{u}_1(\tau)^H \mathbf{P}\mathbf{x}_c\}}{\|\mathbf{P}\mathbf{u}_1(\tau)\|}, \tag{3.40}$$

where the operator $\Re\{.\}$ takes the real part of a complex number. An AML solution can be obtained by assuming that the projection of the $\mathbf{u}_1$ in the interference noise subspace is constant [104]:

$$\hat{\tau}_1 = \arg\max_{\tau} \Re\{\mathbf{u}_1(\tau)^H \mathbf{P}\mathbf{x}_c\}. \tag{3.41}$$

An analytical performance bound is derived for the AML estimator when the propagation delays are integer multiples of the chip period. Perfect power control is assumed in the simulations.

A frequency domain code-timing acquisition method for long-code CDMA is proposed in [189]. The received data given in (3.5) is split into N overlapping blocks of size $(M_0+1)N_cQ$, $\mathbf{x}_\mu = [x_\mu(0), \ldots, x_\mu((M_0+1)N_cQ-1)]^T$ $(\mu = 0, \ldots, N-1)$, where M_0 is a parameter chosen so that the interference between two consecutive blocks is small. Likewise, let $\mathbf{s}_{k,\mu}[i]$ and $\mathbf{w}_\mu$ be $(M_0+1)N_cQ \times 1$ vectors formed from samples of $s_{c,k}(n-i-\tau_k)$ and $w(n)$ respectively. By assuming that the channels are time invariant, the system model for the μ-th block can be written as:

$$\mathbf{x}_\mu = \sum_{k=1}^{K} \sum_{i=0}^{L_h-1} h_k(i)\mathbf{s}_{k,\mu}[i] + \mathbf{w}_\mu, \quad \mu = 0, \ldots, N-1, \tag{3.42}$$

where L_h is the CIR length. The data blocks are converted to frequency domain via DFT:

$$\mathbf{X}_\mu = \mathcal{F}\{\mathbf{x}_\mu\} = \sum_{k=1}^{K} \sum_{i=0}^{L_h-1} h_k(i)\mathcal{F}\{\mathbf{s}_{k,\mu}[i]\} + \mathbf{W}_\mu, \tag{3.43}$$

where $\mathcal{F}\{.\}$ denotes the DFT and $\mathbf{W}_\mu$ is the noise DFT. Using the time-shifting property of the DFT, the frequency domain data vector can be written as:

$$\mathcal{F}\{\mathbf{s}_{k,\mu}[i]\} = \mathrm{diag}\{\bar{\mathbf{S}}_{k,\mu}\}\mathbf{a}_{k,i} = \mathbf{S}_{k,\mu}\mathbf{a}_{k,i}, \tag{3.44}$$

where $\bar{\mathbf{S}}_{k,\mu}$ is the DFT of the data vector formed from M_0N_cQ samples of $s_{c,k}(n)$ and the vector $\mathbf{a}_{k,i}$ is defined as:

$$\mathbf{a}_{k,i} = \left[1, e^{-j\frac{2\pi(i+\tau_k)}{(M_0+1)N_cQ}}, \ldots, e^{-j\frac{2\pi(i+\tau_k)[(M_0+1)N_cQ-1]}{(M_0+1)N_cQ}}\right]^T \tag{3.45}$$

The equation (3.43) can be also be rewritten as:

$$\mathbf{X}_\mu = \sum_{k=1}^{K} \mathbf{S}_{k,\mu}\mathbf{A}(\tau_k)\mathbf{h}_k + \mathbf{W}_\mu, \tag{3.46}$$

where $\mathbf{A}(\tau_k) = [\mathbf{a}_{k,0}, \ldots, \mathbf{a}_{k,L_h-1}]$ and $\mathbf{h}_k = [h_k(0), \ldots, h_k(L_h-1)]^T$. The frequency domain received data consists of a group of K (corresponding to the K users) weighted complex sinusoids $\mathbf{A}_k$ contaminated by noise. The frequencies of the sinusoids are determined by the code delay while the complex amplitudes are determined by the attenuation parameters of the channels. A least square error criterion, non-linear in τ_k and linear in $\mathbf{h}_k$, is invoked to fit the unknown parameters to the observed data [189]:

$$C_{nlls}(\tau_k, \mathbf{h}_k) = \sum_{\mu=0}^{N-1} \left\| \mathbf{X}_\mu - \sum_{k=1}^{K} \mathbf{S}_{k,\mu} \mathbf{A}(\tau_k) \mathbf{h}_k \right\|^2 \tag{3.47}$$

The LS cost function is highly non-linear in τ_k and cannot be easily minimized except where there is a small cell load. An SIC technique with power ranking suggested in [183] is modified and used to solve iteratively the cost function of (3.47). The parameters for the first user are estimated, then its contribution is subtracted from the received signal. In the second step, the parameters for the second user are estimated, then they are used to refine the first user estimated parameters. Iterations are performed between the two steps until the estimated parameters converge. The procedure is repeated for the remaining users. Even though the method is derived for multi-path channels, only frequency flat channels are actually considered in the simulations. It may be possible that the frequency selectivity of the channels degrades the overall algorithm performance. Despite the fact that the above approach is much simpler than the direct optimization approach of the LS cost function, the method still has a high degree of computational complexity, especially for highly loaded cells.

Xiao and Ström [199] investigate the delay acquisition problem for orthogonally modulated signals. The system resembles the uplink in IS-95 system where concatenated Walsh codes and long scrambling codes are used. This work extends the work of [198] where an adaptive algorithm for the estimation of the errors in synchronization was proposed in a synchronized (downlink) transmission scenario. Periodic spreading codes are assumed for the delay estimation stage, even though the system model is derived for long-code CDMA. In this context the performance of several delay acquisition methods are compared. Given enough training symbols, the subspace method of [161] and the linear MMSE delay estimator of [209] outperform the conventional sliding correlator in MUI environments.

Delay tracking using recursive estimators

Commonly, delay tracking techniques assume that the propagation delay was acquired a priori. Delay acquisition methods that are designed for short-codes and cannot be used for long codes are often mentioned [85, 128, 144, 160, 161, 209] in the in the context of long-code CDMA. This is a common mistake among papers dealing with delay tracking in long-codes. However, delay tracking is nevertheless an important issue in relation to the design of DS-CDMA receivers.

Adaptive techniques for delay and data detection are proposed by Lim and Rasmussen [92] for flat fading channels. The tracking of the time variations in the users' delay and the channels is considered while their initial acquisition is not discussed. It is assumed to be performed a priori. The system model is described by the equation (3.5) when $L_h = 1$, $Q = 1$, and the propagation delay is time varying. The parameter vector is defined as:

$$\theta[n] = [h_1(n), \ldots, h_K(n), \tau_1(n), \ldots, \tau_K(n)]^T. \tag{3.48}$$

An RLS filter is employed to track the parameter vector.

Furthermore, the vector $\theta[n]$ is assumed to vary in time according to a first-order Gauss-Markov process:

$$\theta[n+1] = \alpha\theta[n] + \mathbf{z}[n], \tag{3.49}$$

where $\mathbf{z}[n]$ is the zero-mean white process noise with the known covariance matrix $\mathbf{Q}$ and α is considered to be equal to 1. Using equations (3.5) and (3.49), an Extended Kalman Filter (EKF) is employed to track the delays and the time variations of the channels. When the parameter of interest changes rapidly as a function of time, the RLS based method loses the track. The EKF has a much better tracking performance due to parameter modelling. RLS and EKF tracking methods are developed for frequency non-selective channels and cannot be applied directly for multipath channels.

Iltis proposes [67] an EKF-based algorithm for delays and channel tracking for multipath channels. Additionally to the channel and delay tracking, an MMSE data detector is derived. This work improves the work of [68] by significantly reducing the algorithm complexity. In [68] 2^{2K} EKF's are necessary to track the parameters of the K users, whereas in [67] only K EKF's are needed. The system model is described by (3.5) with $Q = 1$. The k-th user parameter vector to be tracked is defined as:

$$\begin{aligned} \mathbf{y}_k[n] &= [h_k(n,0), \ldots, h_k(n, Lh-1), \tau_1(n), \ldots, \tau_K(n)]^T \\ \mathbf{y}_k[n+1] &= \mathbf{F}_s \mathbf{y}_k[n] + \mathbf{z}_k[n+1], \end{aligned} \tag{3.50}$$

where $\mathbf{F}_s$ is the state transition matrix and $\mathbf{z}_k[n+1]$ is i.i.d. a Gaussian distributed process noise vector with a known covariance matrix, $\mathbf{Q}$.

The contribution of the k-th user in the received signal is described by a non-linear function $\mathcal{S}_k$ of the multi-path channel, propagation delay and spreading code as follows:

$$\mathbf{x}_k[m] = \mathcal{S}_k\left(\mathbf{c}_k[m], \mathbf{y}_k[n]\right) b_k(m) + \mathbf{v}_k[m], \tag{3.51}$$

where $\mathbf{v}_k[m]$ is the sum of MUI and thermal noise $\mathbf{w}_k[m]$ as seen by the user k during the m-th symbol.

Based on the equations (3.50) and (3.51) an EKF can be employed to track the k-th user parameter vector time variations. The MUI plus thermal noise vector $\mathbf{v}_k[m]$ is modeled as colored Gaussian noise. The noise statistics are estimated by using the estimates of the channels and delays from all the EKF's. The algorithm is sensitive to the quality of the channel and delay estimates as well as to their initial acquisition. If the delay acquisition is poorly performed, the MUI statistics are incorrectly estimated and a loss in performance is experienced. A common impairment of the EKF methods is the relatively high SNR required, since it may diverge at low SNR. When working at chip level, this is a critical problem since the chip signal is very weak, usually at the additive noise level. The state transition matrix in the state-space equations is usually assumed to be known. In wireless communications the channel is not directly observable and therefore an erroneous state transition matrix may cause the algorithm divergence.

DLL delay tracking

Another category of receivers use delay locked loops (DLL) to track the delay time variations. These methods stem directly form the chip matched filter (CMF). The basic premise of CMF was presented at the beginning of Section 3.3.1. The DLL computes the correlation of the received signal with the spreading code at two time instances: an early correlation and a late correlation. The difference between these correlation values drives a voltage controlled oscillator (VCO) which generates the code chip sequence at the receiver with different delays. The DDL, as with the CMF, is highly sensitive to the near-far effect. Moreover, the majority of methods proposed to overcome the inadequacies of CMF (see [81, 110] and references herein) are either incompatible or have a high degree of computational complexity in the context of long-code CDMA.

Yoon and Leib [205] propose an improved single-user delay locked loop and detection technique for long-code CDMA, using a time-invariant filter to maximize the output SNR. The interfering users' propagation delays and powers are assumed to be known. The method is known as chip-delay locked matched filter (CLMF) and exploits the fact that when the interfering users' chip delays are tracked, the MAI in long-code CDMA can be modeled as a wide-sense cyclostationary (WSCS) process. A single-user detector that is robust with regard to near-far effects and which does not require the knowledge of the other users spreading codes is produced. However, the performance of the method depends strongly on the knowledge of the interfering users' delays. A greater than 5% root-mean-square error in delay estimation translates into a severe performance degradation.

Discussion

The delay estimation issue in long-code CDMA has not received as much research interest as has been the case for short-codes. The long-code DS-CDMA signal, unlike the short-code DS-CDMA signal, contains very little statistical information that can be used for delay estimation. Unrealistic assumptions are usually made when dealing with long-codes. For example, the approximate ML method of [104] assumes that the delays are integer multiples of the chip period. The interfering users are assumed to be already synchronized and the channels are also assumed to be flat fading channels. Moreover, perfect power control is considered in the simulations. These assumptions violate many of the DS-CDMA systems characteristics and therefore the method is of little practical interest.

The frequency domain method of [189] is derived for frequency selective channels, but its performance is presented only for frequency-flat channels. One may be suspicious that the channels frequency selectivity affect the receiver performance. The computational complexity of the algorithm becomes prohibitive for heavy loaded cells. Both methods [104, 189] require the knowledge of the transmitted data over the observation interval.

Another problem which arises in realistic mobile communication scenarios is the time variation of the delays. This problem is usually solved by employing tracking mode receivers. The DLL based delay estimators suffer from MUI and near-far effects. The recursive tracking methods based on EKF deliver a performance superior to the DLL tracking loops. Moreover, they exhibit improved resistance to near-far effects and interference. All the delay tracking methods are very sensitive to the delay initial acquisition. They usually assume that the delays are correctly acquired using existing delay acquisition methods and methods developed for short-code are usually mentioned [67]. However, these methods are usually impossible to accommodate to long-code systems. The EKF based methods [92, 67] may suffer also from modeling errors. They assume the knowledge of the state-space model statistics and therefore are sensitive to any mismatch.

The classification of the delay estimation techniques for long-code DS-CDMA according to several criteria is presented in Table 3.3.

3.3.2 Receiver algorithms

Receiver structures designed for short-codes are very difficult to accommodate in long-code systems. In this section receiver algorithms suitable for long-code DS-CDMA are reviewed. ML receivers are first presented, then several interference cancellation techniques are described. LS channel estimation methods are presented. Blind receiver approaches are briefly introduced.

The tracking mode receivers based on EKF and RLS presented in the delay estimation section can also be seen as receiver algorithms since they also estimate the channels. This

	ML [104]	**Frequency domain LS** [189]	**EKF and RLS tracking** [92, 67]	**DLL tracking** [205]
Side info	Data-aided, synchronized interference	Data-aided	Data aided, known stat. of the channel model, delays acquired a priori	Data-aided, delays acquired a priori
Performance	Robust to large cell load and high NFR	Robust to large cell load and high NFR	Robust to large cell load and high NFR, sensitive to initial delay acquisition	Sensitive to large cell load and NFR, sensitive to initial delay acquisition
Complexity	Moderate	High	High	Low
Channel cond.	Freq. flat time invariant	Freq. selective time invariant but in simulations only frequency flat	Freq. selective fading	Freq. selective fading

Table 3.3: The classification of the delay estimation algorithms for long-code DS-CDMA

is especially so for the algorithm of [67], where a MMSE detection method is also proposed, in addition to channel and delay tracking. The bit error rate (BER) performance of the MMSE detector is evaluated analytically and experimentally [67].

ML channel estimation

An ML channel estimator is proposed by Bhashyam and Aazhang in [13]. The users' channel impulse responses are collected in an unknown vector $\mathbf{h} = [\mathbf{h}_1^T, \ldots, \mathbf{h}_K^T]^T$. Assuming that the maximum propagation delay is N_c, the received signal during the i-th bit is described by:

$$\mathbf{x}_i = \mathbf{C}_i \mathbf{B}_i \mathbf{h} + \mathbf{w}_i, \tag{3.52}$$

where $\mathbf{C}_i$ is the code matrix comprised of the right part of the spreading code for the i-th bit and the left part of the spreading code for the $i+1$ bit. $\mathbf{B}_i$ is the matrix of the transmitted bits and $\mathbf{w}_i$ is the additive Gaussian noise. It is assumed that the joint conditional distribution of the observation vectors given the knowledge of the spreading codes, transmitted data and channels is Gaussian. Therefore, the ML estimate of the $\mathbf{h}$

given L known training symbols is:

$$\hat{\mathbf{h}}(L) = \left[\sum_{i=1}^{L} (\mathbf{C}_i\mathbf{B}_i)^H (\mathbf{C}_i\mathbf{B}_i)\right]^{-1} \left[\sum_{i=1}^{L} (\mathbf{C}_i\mathbf{B}_i)^H \mathbf{x}_i\right]. \tag{3.53}$$

The CIRs are considered to be invariant over the duration of L symbols. The computation of the channel estimates requires the inversion of a large matrix, which is a computationally demanding operation. The authors propose two adaptive methods for the channel estimation, in order to avoid the large matrix inversion. One is a stochastic gradient method with a fixed step size, while the other is a steepest descent method with a variable step size. The steepest descent method converges more quickly than the stochastic gradient method at the cost of increased computational complexity. Combined with a recursive estimation of the matrices in (3.53), the adaptive methods achieve almost the same performance as the block ML scheme. The steepest descent method achieves the same performance as the block ML for a sufficiently large enough sample size at the cost of increased complexity in the computation of the variable step size. When some a priori information regarding the CIR's is available, the complexity of the algorithms may be decreased by reducing the dimension of the system model. Assuming that the channels are slowly time varying, the adaptive estimators are shown to be able to track the time variations in the channels in simulation.

Interference cancellation

Linear interference cancellation techniques may be promising detection techniques for long-code CDMA because they do not usually make any assumptions about the periodicity of the spreading codes. The PIC method of Varanasi and Aazhang [180], is further improved and analyzed. It is proved in [51], that for short spreading codes with a given number of cancellation stages, a unique choice of weights exists that leads to the minimum achievable MSE. Under these conditions, the weighted linear PIC is equivalent to the steepest descent algorithm. In long-code systems the optimal set of weights that leads to a minimum achievable MSE must be recomputed for each symbol, making the computational complexity of the algorithm prohibitive for practical implementation. In [50], a linear PIC for long-code CDMA is proposed to overcome this problem. A fixed set of optimum weighs is computed which gives the best average performance over the long codes. For a certain transmitted symbol, the output decision statistics for all the K users at the i-th iteration of the weighted m stages PIC is given by:

$$\mathbf{r}_i = (\mathbf{I} - \mu_i (\mathbf{R} + \alpha\mathbf{I}))\, \mathbf{r}_{i-1} + \mu_i \mathbf{C}^H \mathbf{y}, \tag{3.54}$$

where $\mathbf{C}$ is the matrix formed from the K code-word vectors, $\mathbf{y}$ is the received signal vector, μ_i and α are the set of weights and $\mathbf{R} = \mathbf{C}^H\mathbf{C}$ is the instantaneous code correlation matrix. The excess error of the PIC is shown to depend on the eigenvalues of the matrix $\mathbf{R}$ and the PIC weights μ_i and α. When the excess error is minimized averagely over the long codes, the PIC weights are found to depend on the first $2m$ moments of the eigenvalues of the spreading code correlation matrix. Exact methods for deriving the moments of the eigenvalues are also provided, based on a polynomial extension. The method is derived for AWGN channels only. Another major impairment is that the system is considered to be perfectly synchronized. It is not clear how the multipath propagation and the error from the delay estimation influence the performance of the algorithm.

In [113] a linear estimation technique for long-code CDMA was proposed. It can be used to improve the BER performance of the interference cancellation schemes in AWGN channels. The cross-correlation between the code of a particular interfering user with that of the desired user is computed. The key idea is that multiplying the cross-correlation with the output of the matched filter receiver for the interfering user preserves information about the desired user signal. Prior to a multistage interference cancellation technique, the outputs of the K-th matched filters are optimally combined in order to obtain the maximum SNR:

$$\bar{u}_p(i) = \sum_{k=1}^{K} \theta_{k,p}^{*} u_k(i) \rho_{k,p}(i) = \theta_P^H \mathbf{x}_p[i], \tag{3.55}$$

where $u_k(i)$ is the matched filter output for the i-th symbol of the k-th user and $\rho_{k,p}(i)$ is the cross-correlation between the users k and p. By defining the vectors:

$$\tilde{\theta}_p = \begin{pmatrix} \Re\{\theta_p\} \\ \Im\{\theta_p\} \end{pmatrix} \qquad \tilde{\mathbf{x}}_p[i] = \begin{pmatrix} \Re\{\mathbf{x}_p[i]\} \\ \Im\{\mathbf{x}_p[i]\} \end{pmatrix} \tag{3.56}$$

the optimum weights are:

$$\tilde{\theta}_p = \frac{\kappa \mathbf{R}_{\tilde{x}}^{-1} \tilde{\mathbf{d}}_p}{1 - A_p^2 \tilde{\mathbf{d}}_p^H \mathbf{R}_{\tilde{x}}^{-1} \tilde{\mathbf{d}}_p}, \tag{3.57}$$

where $\mathbf{R}_{\tilde{x}} = E[\tilde{\mathbf{x}}_p[i]\tilde{\mathbf{x}}_p^H[i]]$ and $\tilde{\mathbf{d}}_p$ is a vector with all elements equal to $1/N_c$ except for the p-th element which is equal to 1. A_p is the amplitude of the p-th user signal. In order to obtain the optimum combiner, a matrix inversion operation is necessary. To avoid the matrix inversion, a blind adaptive method for the same linear estimation technique was proposed in [112]. The blind adaptive solution is found by minimizing a constrained minimum output energy (CMOE) criterion, that is:

$$\begin{aligned} \text{Minimize :} \qquad & E[|\tilde{\theta}_p^H \tilde{\mathbf{x}}_p[i]|^2] \\ \text{Subject to :} \qquad & \tilde{\theta}_p^H \tilde{\mathbf{d}}_p = 1 \end{aligned} \tag{3.58}$$

The solution to the optimization problem is found adaptively using a weighted recursive algorithm. It is shown that when used as the first stage of a linear or non-linear PIC, the method leads to significant gains in BER performance.

A single stage of a linear canceler gives large gains over a matched filter estimator for under-loaded systems (the number of active users is considerably lower than the spreading factor). In [65] the performance of the SIC is studied using the graph theoretical approach. The theoretical results obtained here match very well with the experimental results. Significant performance degradation is observed in comparison to the matched filter when the number of users exceeds a certain limit. It is also assumed that the channels and users' delay are accurately known, therefore the interference cancellation is performed coherently. A significant loss in SIC performance is expected when these parameters are not estimated exactly.

LS channel estimation

In [22] an LS method for channel estimation in long-code DS-CDMA is proposed. The effect of the delay is included in the CIR by assuming that the maximum propagation delay is one symbol period. Assuming also the availability of a training sequence, batch and adaptive channels estimators are derived. The resulting solution is similar to the ML method of [13].

The channel estimation problem is performed in both a decentralized and centralized manner. The adaptive channel estimator is implemented using a steepest-descent algorithm. The channel estimates are used in a SIC scheme for data detection. The same idea for parameter estimation is used in [23]. The more general problem of estimating delays, angles of arrival (AoA) and channels is considered in a scenario where array antennas are used at the receiver. The unknown parameters are contained in constant vectors. These vectors are estimated using the same procedure as in [22]. The estimates are further used to obtained the delays, AoA and channels. The algorithm BER performance is studied by using linear MMSE detectors based on the estimated parameters. Moreover, CRLB on the error variance of any joint parameter estimation procedure is derived exploiting the known training sequence. The main drawback of this algorithm is that it is only derived for frequency flat channels.

Blind receivers

Blind receivers are in general attractive solutions since no training data is required. In uplink CDMA the users' spreading codes are known to the receiver. Therefore, this information is used when deriving blind receiver techniques. The blind MMSE receivers offer robustness against near-far effects and noticeable performance gains over the single-user matched filter receivers. The blind subspace based methods can provide solutions that converge on the trained MMSE receiver in a dispersive environment [43, 44]. They rely on subspace properties which require the noiseless autocorrelation matrix to lose rank. This restricts their applicability to systems that are not overloaded. Therefore blind techniques are more likely to be used as a start-up efficient technique which is then switched to DD methods after the cell becomes heavily loaded [61].

Xu and Tsatsanis propose a blind channel estimator for long-code DS-CDMA in [200]. The users' propagation delays are assumed to be known and the CIR's are assumed to be stationary. The algorithm is based on matching the output signal covariance matrix parameterized by the users CIR with its instantaneous approximation. The resulted cost function can be minimized in two ways: a batch computationally expensive method and an adaptive stochastic gradient method. The identifiability problems of the batch method are discussed as well as the convergence of the adaptive approach in mean sense.

Zhang and Tsatsanis [207] propose a blind start up algorithm for MMSE receivers in CDMA. The method is initially developed for short-code systems but an extension to long codes is also discussed. The technique is based on the fact that the observed data auto-correlation matrices before and after a new user is accepted in the system differ by only a low rank matrix that is contributed by the autocorrelation of the new user's signal. When long-codes are used, the user signature is time varying and a pre-processing stage is needed to transform the random signature into a time-invariant one. The received signal vectors are multiplied with the transpose conjugate of the code matrix. If the spreading codes take the values ± 1, the system model is equivalent to the short-code system model, therefore the proposed method for signature identification can be applied. The blind MMSE method proposed here would be the optimum combining technique of a RAKE-like receiver in long-code CDMA. The optimality is in the sense of maximum SNR at the combiner output.

A blind deterministic approach to symbol estimation is proposed by Leus and Moonen in [82]. When the processing is performed on short blocks of the received signal, deterministic approaches generally have a better performance than stochastic schemes. Two approaches are considered: a sub-space based method and a linear equalizer. The estimation of the transmitted data from a perfectly synchronized single user of interest is considered.

A blind Baysian multiuser receiver for asynchronous long-code CDMA in multipath channels and white Gaussian noise is proposed in [203]. This method is further improved in [204]. In addition to the additive noise, out-of-cell interference is considered as well as narrow band interference. The multiuser detector is based on the idea that the total noise plus interference can be modelled as colored Gaussian noise from some unknown statistics. However, a priori knowledge of the distributions for the unknown channels and noise covariance matrix are assumed. The proposed method is also suitable for iterative Turbo processing.

Concluding remarks

The long-code DS-CDMA system is characterized by a time varying spreading code. Therefore, receiver structures developed for short-code DS-CDMA systems are difficult to accommodate in long-code systems. Their complexity increases significantly since computationally demanding operations (large matrix inversions) have to be performed for every sampling instance.

The block ML channel estimator of [13] is able to achieve the CRLB if sufficient training data is available. The computational complexity of the algorithm is prohibitive. This can be further reduced by adopting adaptive implementations of the algorithm.

The channel estimation methods for long-code systems usually assume that the propagation delays are in an uncertainty period of one symbol period [22, 23] and the effect of the delay is included in the CIR vector. The resulting channel and delay vector is estimated using different approaches assuming the knowledge of the transmitted data. The estimates are used directly for data detection [22] or the delays and channels are explicitly derived [23]. This approach is of great practical interest since the delay and channel estimation are performed jointly. A similar approach is adopted by the methods proposed in this thesis and it will be further discussed in Chapter 4.

The channel estimation algorithms [13, 22, 23] assume the channels are stationary over the observation interval. When adaptive implementations are possible, they can track only very slow time-variations of the channels. Simulations results in these papers indicate that these methods may be used only in very low mobility scenarios.

The SIC and PIC methods are usually used in conjunction with one of the channel estimators mentioned in the previous paragraphs. Providing good parameter estimates, the IC methods deliver a reliable performance. They offer large gains over the conventional RAKE receiver at comparable levels of computational complexity.

Blind methods are difficult to use in long-code CDMA since there is little statistical information that can be exploited in the signals. However, stochastic and deterministic blind receivers are proposed. They usually suffer from slow convergence and their performance is degraded in over-loaded cells . However, blind methods may be used as a start-up stage for conventional training based receivers when there are few active users in the cell [200].

As a general conclusion, the long-code receivers suffer from increased computational complexity when compared to short-code receivers. This is due to the time varying spreading code. However, the practical cellular systems based on DS-CDMA are long-code systems and further investigation of such methods is needed.

A general classification of the channel estimation methods proposed for long-code DS-CDMA is presented in Table 3.4.

	ML channel estim. [13]	**LS channel estim.** [22, 23]	**Blind methods** [200, 82]
Training data	Data-aided	Data-aided	No training, require synchronization
Performance	Robust to large cell load and NFR	Robust to large cell load and NFR	Robust to NFR but sensitive to large cell load, remaining ambiguities
Complexity	High, lowered using adaptive implementation	High, lowered using adaptive implementation	High
Channel cond.	Freq. selective time-invariant	Freq. selective time invariant	Freq. selective time invariant

Table 3.4: The classification of the channel estimation algorithms for long-code DS-CDMA

3.4 Discussion

Uplink DS-CDMA receivers have complicated structures because they perform the synchronization also in addition to data detection. Most of the research work related to this subject deals with periodic spreading codes. The periodic code induces cyclostationarity into the signals. This property if often used in synchronization [160, 161, 209] as well as in data detection [9, 125]. These methods are more robust in face of interference and near-far effects than the traditional correlation based approaches [129].

The cyclostationarity of DS-CDMA signals is destroyed when long-codes are employed. The spreading code is different for each information symbol. Consequently, the synchronization and data detection methods designed for short-codes cannot be directly applied in long-code systems. Algorithms which take into account the long-code CDMA system properties are of great interest. The long-code CDMA system model is more complex. There are very few approach to the delay acquisition problem in the literature. They are often derived assuming unrealistic conditions for the DS-CDMA system: perfect power control, symbol level synchronization, flat fading channels. Therefore the practical interest for these methods is rather low.

The channels are assumed to be stationary in order to apply standard ML [13, 104] or LS [22, 23] estimation techniques. This approach limits the applicability of the algorithms to low mobility scenarios, where the Doppler spread is small and time variations of the channels are very slow. In high mobility scenarios, or when the carrier frequency is high, channel and delay tracking methods are needed [67]. The tracking mode receivers based on recursive estimators are sensitive to initial acquisition of the parameters. The DLL based tracking mode receivers suffer from low immunity to interference and near-far effects.

IC methods [187, 180] can be accommodated in both short and long-code CDMA systems. These methods are more practical alternatives to the high complexity MUD [183]. IC methods provide flexible solutions. They can be implemented using adaptive channel estimators allowing for the tracking of channel time variations. They need reliable estimates of the channels and delays in order to deliver a good level of performance.

Blind receiver structures constitute an attractive solution since no training data is needed. In CDMA knowledge of the spreading codes is valuable information that is used by the majority of the proposed blind algorithms. Most of the blind methods are proposed for short-codes. Some of them are also adapted for long-codes [207]. However, their performance is usually limited to under-loaded cells and low mobility scenarios. Inherent ambiguities are often in the form of a complex ambiguity matrix. This problem is difficult to solve and requires additional high computational complexity algorithms.

Several practical issues have to be considered when designing a reliable up-link DS-CDMA receiver: the channels are time-variant frequency selective; the power control is imperfect; the spreading codes are not perfectly orthogonal. If the system uses long-codes, this information also has to be taken into account. The receiver has to deliver reliable performance for all the users regardless the channel conditions they experience. Using multiantenna systems allows for an increase in receiver performance by taking advantage of both spatial diversity and increased SNR. The operations performed at the receiver have to use as little training data as is possible while using additional statistical information as well as structural information of the DS-CDMA signals.

Chapter 4

Adaptive receiver for long-code asynchronous DS-CDMA

In this chapter the author's contributions in designing a long-code DS-CDMA receiver are presented. The ideas in the proposed algorithms are introduced and the main results and contributions are highlighted. Detailed mathematical derivations of the algorithms as well as simulation results can be found in *Papers III-VIII.*

A cellular long-code DS-CDMA network is considered in this thesis. Firstly, the general assumptions under which the algorithms are derived are presented:

- The transmitted data bits are uncoded. They are mapped into a QAM constellation before transmission. A training sequence with limited length is available at the receiver, for each user.
- The channels are assumed time and frequency selective. For algorithm derivation, the channels are assumed to be generated according to a low order AR dynamic model. In simulations the channels are generated according to a more realistic channel model [58]. The channels are assumed time-invariant over one symbol period.
- The propagation delays are deterministic and fixed over the observation interval.
- The additive noise is i.i.d. Gaussian distributed with zero mean and known variance.
- The transmitted data, the channel impulse responses and the additive noise are statistically independent.
- No prior information on the MUI is assumed.

The assumption of the deterministic and fixed delay is feasible for delay acquisition purposes. Most of the papers in the literature dealing with delay acquisition assume the same characteristics of the delay [104, 160, 161, 189, 209]. If the delay is time-varying, the proposed methods for delay estimation may be used as an initial stage of a tracking mode receiver such as that proposed in [67].

We adopt a centralized approach to the the problem of users parameters estimation. This means that the delays, channels and transmitted data are estimated simultaneously for all the active users in the cell. Another option would be a user-by-user parameters estimation, in a decentralized fashion. Such an approach introduces delays in the data decisions for certain users especially in high mobility scenarios. Therefore, a centralized approach for parameters estimation is preferable in uplink DS-CDMA system.

The uplink in cellular DS-DCMA networks with long spreading codes is considered. K active users transmit their signals spread with codes with processing gain N_c. The BS is equipped with Q receive antennas. The users are sufficiently separated apart, therefore the sub-channels can be assumed as being uncorrelated. With these assumptions the system model is similar to that described in sub-section 3.1.1. The base-band chip rate sampled signal at the q-th received antenna is described by the equation (3.5), repeated here for convenience:

$$x_q(n) = \sum_{k=1}^{K} \sum_{i=0}^{L_h-1} h_{kq}(i,n) s_{c,k}(n - i - \tau_k) + w_q(n), \tag{4.1}$$

where $s_{c,k}(n)$ is the chip sequence corresponding to the k-th user which incorporates the transmitted data, τ_k is the propagation delay corresponding to that user and $w_q(n)$ is the additive i.i.d. Gaussian distributed noise at the q-th antenna elements. The channels impulse responses are the convolution of the chip pulse-shape filter, physical channel and receive filter. The use of multiple antennas at the receiver brings two advantages: receiver diversity through the uncorrelated sub-channels and increased SNR at the receiver. Therefore, even if a sub-channel experiences a deep fade there are always more reliable channels from which the information sequence can be reliably demodulated. The superior performance of the multi-antenna receivers comes at the cost of increased complexity in the algorithms and increased equipment cost.

For a reliable data estimation, the receiver algorithm has to estimate the time-varying CIR $h_{kq}(i,n)$ as well as the propagation delay τ_k corresponding to each user. The proposed adaptive multichannel estimation method is presented in Section 4.1 and several delay estimation strategies are introduced in Section 4.2.

4.1 Stochastic gradient multichannel estimation

The delay of the user k can be rewritten as a sum of its integer part, p_k, and fractional part, d_k, with respect to the chip period T_c:

$$\tau_k = p_k + d_k \tag{4.2}$$

Taking into account that effect of the chip pulse-shape filter effect is absorbed into the channel impulse response, we can define a new input sequence which is synchronous with the received sequence $x_q(n)$:

$$r_{c,k}(n) = (1 - d_k) s_{c,k}(n - p_k) + d_k s_{c,k}(n - p_k - 1). \tag{4.3}$$

Similar signal models are used in the literature [199]. The received sampled sequence at the q-th antenna may be rewritten as:

$$x_q(n) = \sum_{k=1}^{K} \sum_{i=0}^{L_h-1} h_{kq}(i,n) r_{c,k}(n - i) + w_q(n) \tag{4.4}$$

By stacking N_c received samples into a vector $\mathbf{x}_q[n] = [x_q(n), ..., x_q(n - N_c + 1)]^T$, we can write the following matrix form equation:

$$\mathbf{x}_q[n] = \sum_{k=1}^{K} \mathcal{H}_q^{(k)}[n] \mathbf{r}_{c,k}[n] + \mathbf{w}_q[n] \tag{4.5}$$

where $\mathbf{r}_{c,k}[n] = [r_{c,k}(n), \ldots, r_{c,k}(n-N+1)]^T$ with $N = N_c + L_h - 1$, $\mathcal{H}_q^{(k)}[n]$ is the channel convolution matrix from the user k to antenna q of dimension $N_c \times N$ and $\mathbf{w}_q[n] = [w_q(n), ..., w_q(n - N_c + 1)]^T$ is the noise vector.

By stacking the signal vectors from all the receive antennas into a column vector we obtain the following expression:

$$\mathbf{x}[n] = \sum_{k=1}^{K} \mathcal{H}^{(k)}[n]\mathbf{r}_{c,k}[n] + \mathbf{w}[n] = \mathcal{H}[n]\mathbf{r}_c[n] + \mathbf{w}[n] \tag{4.6}$$

where

$$\begin{aligned} \mathcal{H}^{(k)}[n] &= [\mathcal{H}_1^{(k)T}[n], \ldots \mathcal{H}_Q^{(k)T}[n]]^T \\ \mathcal{H}[n] &= [\mathcal{H}^{(1)}[n], \ldots \mathcal{H}^{(K)}[n]] \\ \mathbf{r}_c[n] &= [\mathbf{r}_{c,1}^T[n], \ldots, \mathbf{r}_{c,K}^T[n]]^T \\ \mathbf{w}[n] &= [\mathbf{w}_1^T[n], \ldots, \mathbf{w}_Q^T[n]]^T. \end{aligned} \tag{4.7}$$

It is assumed that the maximum delay propagation is M chip periods. In the literature this value is usually considered to be less than N_c. In the proposed algorithm an arbitrarily large M may be used. However, it increases the overall algorithm complexity. For reasons of computational complexity, we assume that $M = N_c$. This assumption is reasonable because a coarse synchronization may be performed a priori the users transmission using the network signalling. Then we can write in matrix form for user k:

$$\mathbf{s}_{c,k}[n - p_k] = B_{p_k}\mathbf{s}_k[n] \tag{4.8}$$

where $\mathbf{s}_k[n] = [s_{c,k}(n), \ldots, s_{c,k}(n - N - M + 1)]$ and the matrix B_{p_k} is defined as:

$$B_{p_k} = \begin{bmatrix} \mathbf{0}_{N\times p_k} & \mathbf{I}_N & \mathbf{0}_{N\times(M-p_k)} \end{bmatrix} \tag{4.9}$$

where $\mathbf{0}_{m\times p}$ is the zero matrix of dimension $m\times p$ and $\mathbf{I}_m$ is the identity matrix of dimension $m \times m$. By taking into account that:

$$\mathbf{r}_{c,k}[n] = (1 - d_k)\mathbf{s}_{c,k}[n - p_k] + d_k\mathbf{s}_{c,k}[n - p_k - 1] \tag{4.10}$$

the equation (4.6) can be rewritten as:

$$\begin{aligned} \mathbf{x}[n] &= \sum_{k=1}^{K} \mathcal{H}^{(k)}[n]\left((1 - d_k)B_{p_k} + d_k B_{p_k+1}\right)\mathbf{s}_k[n] + \mathbf{w}[n] = \\ &= \sum_{k=1}^{K} \mathcal{H}^{(k)}[n]B_k\mathbf{s}_k[n] + \mathbf{w}[n] = \\ &= \mathcal{H}[n]B\mathbf{s}[n] + \mathbf{w}[n] = C[n]\mathbf{s}[n] + \mathbf{w}[n], \end{aligned} \tag{4.11}$$

where $B = \text{Diag}\,[B_1, \ldots, B_k]$ is the block diagonal matrix of the propagation delay matrices of individual users and $\mathbf{s}[n] = \left[\mathbf{s}_1^T[n], \ldots, \mathbf{s}_K^T[n]\right]^T$. Instead of explicitly estimating the channel matrix and the propagation delays we estimate the matrix $C[n] = \mathcal{H}[n]B$ which contains both the channel and delay information.

The channel taps are usually modeled as circular complex Gaussian processes in order to model the Rayleigh and Ricean fading [21]. A model of the channel dynamics description can be employed to develop more accurate tracking algorithms. Low order AR models are widely used in the literature [67, 78, 170]. Uncorrelated channel taps are assumed in [67, 78] while in [170] the more general case of correlated channel taps was considered. The AR model parameters are shown to be directly related to the channels Doppler spread and therefore to their dynamics [78]. In our approach we use similar dynamic model to [67, 78] to describe the channels time evolution, but extended to the multiuser case.

The matrix $\mathcal{H}[n]$ contains all the channel taps at time instances from n to $n - N_c + 1$. Let us assume that the time evolution of the channels may be described by the following discrete-time dynamic system model:

$$\mathcal{H}[n] = \mathcal{H}[n-1]\mathcal{A} + \mathcal{W}[n]. \tag{4.12}$$

The matrix $\mathcal{W}[n]$ is the process noise matrix and it is considered to be independent of $\mathcal{A}$ and $\mathcal{H}[n]$. As the sub-channels are considered to be independent, the matrix $\mathcal{A}$ is a diagonal matrix.

Using Equation (4.11), we estimate the matrix $C[n]$ instead of $\mathcal{H}[n]$ in order to avoid the explicit estimation of the propagation delays. Since the delay matrix B is constant and deterministic we consider that $C[n]$ may be described by a similar dynamic system model:

$$C[n] = C[n-1]\mathcal{A}_1 + \mathcal{W}_1[n] \tag{4.13}$$

The channel estimation algorithm objective is to find an estimate of $C[n]$ that minimizes the MSE:

$$\mathcal{J} = tr\left[E\left\{(\mathbf{x}[n] - C[n]\mathbf{s}[n])\,(\mathbf{x}[n] - C[n]\mathbf{s}[n])^H\right\}\right], \tag{4.14}$$

where the operator $tr[.]$ stands for the trace of a matrix.

Our channel estimator falls in the category of MMSE estimators. If the channels are time-invariant the output signals statistics are wide sense stationary and the optimal solution is the Wiener filter [54]. In this thesis the channels are assumed time-varying and the output signals statistics are non-stationary. In this case, the optimum linear minimum variance channel estimator is the Kalman filter [54]. In order to apply the Kalman filter, the statistics of the channel state-space model have to be known. This is a critical problem since the channels are not directly observable. Therefore, we prefer to use a sub-optimal solution but which requires less prior information on the channels statistics.

A stochastic gradient algorithm is obtained if the instantaneous squared error of (4.14) is minimized adaptively. Using the complex valued matrix derivative properties [52, 54], and assuming that the channel matrix and the transmitted sequences are independent the following update rules are obtained:

$$\begin{aligned} \mathbf{e}[n] &= \mathbf{x}[n] - \hat{C}[n]\mathbf{s}[n]; \\ \hat{\mathcal{A}}_1[n+1] &= \hat{\mathcal{A}}_1[n] + \Delta_1 \hat{C}^H[n-1]\mathbf{e}[n]\mathbf{s}^H[n]; \\ \hat{C}[n+1] &= \hat{C}[n]\hat{\mathcal{A}}_1[n+1] + \Delta\mathbf{e}[n]\mathbf{s}^H[n]. \end{aligned} \tag{4.15}$$

The data vectors $\mathbf{s}[n]$ contain the training data sequence. After the training period, data decisions from the receiver algorithm will be used instead, in a decision-directed mode.

In order to ensure the convergence of the algorithm, an appropriate range for the step-size parameters Δ and Δ_1 has to be determined. For analysis purposes we assume that the channels are time invariant over the observation interval. We need to determine how to choose the step size parameter Δ so that the algorithm converges in mean sense. The Wiener solution of the channel estimate is found by minimizing the mean square error

Step 1:	**Initialization**
	Choose the values of Δ,Δ_1,$\hat{\mathcal{A}}_1[0]$, initialize $\hat{C}[0]$ with random value, set the length of the training sequence N_{tr}
Step 2:	**Data aided mode**
	for $n \leq N_{tr}$,
	Collect the training data in the vector $\mathbf{s}[n]$, collect the received samples in the vector $\mathbf{x}[n]$
	Iterate on the Equations (4.15)
	end
Step 3:	**Decision directed mode**
	for $n > N_{tr}$,
	Collect the data decisions in the vector $\mathbf{s}[n]$, collect the received samples in the vector $\mathbf{x}[n]$
	Iterate on the the Equations (4.15)
	end

Table 4.1: The pseudo-code of the channel estimation algorithm

in Equation (4.14) with respect to the channel matrix. It is proved in *Paper VI* that if the mean squared error of the channel matrix estimate is adaptively minimized, and with a properly chosen step-size parameter, the steepest descent channel matrix estimate converges to the Wiener solution. If the instantaneous squared error of the channel matrix estimate is used instead, the stochastic gradient channel matrix estimate converges in mean to the Wiener solution. The difference between the final (when $n = \infty$) stochastic gradient channel matrix estimate and the Wiener solution, i.e. excess error, is the price paid for using instantaneous error approximation instead of the expected value of the error. The maximum step-size Δ_{max} which ensures that the stochastic gradient algorithm convergences must satisfy the following condition:

$$0 < \Delta_{max} < \frac{2}{\sigma^2_{max}}, \tag{4.16}$$

where σ^2_{max} is the maximum transmit power among the K users.

When the channels are time varying, the tracking capabilities of the algorithm are not only determined by the step-size Δ, but also by Δ_1. In non-stationary conditions the convergence analysis is not feasible since the output signal statistics are not stationary. Hence the choice of the step-size Δ_1 as well as the initial estimate of the matrix $\mathcal{A}_1$ have to be found experimentally. The parameter Δ_1 also depends on the channels, its value increases if the dynamics of the channel matrix increase.

The multi-user channel estimation algorithm pseudo-code is presented in Table 4.1.

In simulations, the channels are generated using the more realistic channel model [58] based on the COST 207 project [114]. Four propagation environments have are described by this model: Typical Urban (TU), Bad Urban (BU), Hilly Terrain (HT) and Rural Area (RU). These propagation environments are determined by individual delay distributions. Measurements have been made over typical bandwidth of 10 to 20 MHz. We consider the TU environment with the delay spread of maximum 5μs. The data bits are transmitted at the rate of 0.2MBps, therefore the delay spread is less than the symbol period.

The performance of the proposed channel estimator is studied by means of MSE. This is the most appropriate performance measure since we are directly interested to evaluate the channel estimator quality in different scenarios. In a realistic scenario the channel estimator MSE cannot be evaluated and other performance measures have to be adopted such as the raw SER at the receiver output. The MSE of the channel estimator is evaluated in different simulations setups with variable length of the training sequence, variable SNR or variable NFR. The simulation conditions and results are presented in details and discussed in *Papers III-VIII.*

In order to study the performance of the proposed channel estimation method an MMSE equalizer is also derived. The objective is to find the equalization matrix $G[n]$ which minimizes the MSE:

$$\mathcal{J}_G = tr\left[E\left\{(G[n]\mathbf{x}[n] - \mathbf{s}[n])\,(G[n]\mathbf{x}[n] - \mathbf{s}[n])^H\right\}\right] \tag{4.17}$$

Differentiating $\mathcal{J}_G$ w.r.t. $G^*[n]$ and setting the derivative to zero we obtain:

$$G[n] = R_{sx}R_{xx}^{-1} \tag{4.18}$$

where R_{sx} and R_{xx} are the input-output cross-correlation matrix and the output covariance matrix, respectively. Assuming that the noise and the information sequences are uncorrelated, the expression for the MMSE equalization matrix can be rewritten as:

$$G[n] = R_{ss}C^H[n]\left(C[n]R_{ss}C^H[n] + \sigma_w^2\mathbf{I}_{QN_c}\right)^{-1}. \tag{4.19}$$

In realistic scenarios the channel matrix $C[n]$ is replaced by its estimate $\hat{C}[n]$.

The channel matrix $C[n]$ has a special structure due to the absorption of the propagation delays. Therefore, the equalization matrix $G[n]$ also has a special structure (see *Paper V* and *Paper VI*). In an ideal case, when the channel matrix is known, the equalized chip sequence vector $\hat{\mathbf{s}}_k[n]$ is given by:

$$\hat{\mathbf{s}}_k[n] = G[n]\mathbf{x}[n] = [0\ldots0\;\; \hat{s}_{c,k}(n-p_k)\ldots\hat{s}_{c,k}(n-p_k-N)\;\; 0\ldots0]^T. \tag{4.20}$$

For despreading we have to know the integer part p_k of the propagation delay τ_k. In the next subsection several strategies for the estimation of the integer part of the propagation delays are introduced. Using the MMSE equalizer the channel estimator performance may be studied using the raw SER.

4.2 Propagation delay estimation

The channel matrix $C[n]$ contains information about the active users' CIRs as well as their propagation delays. Estimating this matrix leads to an implicit estimation of the users CIRs and delays. As was seen in the previous subsection, the channel matrix estimation and MMSE chip-level equalization can be performed without knowledge of the propagation delays. The maximum possible value of the propagation delay is required instead. This value is selected by the algorithm designer, but a rough approximation can be found from the physical dimensions of the cell. The integer part of the propagation delay is only needed for despreading. Several delay estimation methods are introduced next. All of them are deterministic methods. A method based on LS optimization is developed first. Then, a maximum norm algorithm and a maximum energy algorithm are derived. Both of them are based on the structure of the channel matrix. Finally, the delay profile algorithm suitable for adaptive channel estimation is developed.

The matrix $C[n]$ is a $QN_c \times K(M+N)$ block matrix containing channel matrices corresponding to the CIRs and delays:

$$C[n] = \begin{bmatrix} C_1^{(1)}[n] & \dots & C_1^{(K)[n]} \\ \vdots & \vdots & \vdots \\ C_Q^{(1)}[n] & \dots & C_Q^{(K)[n]} \end{bmatrix}. \tag{4.21}$$

The matrix $C^{(k)}[n]$ of size $QNc \times (M+N)$ is considered by taking the columns from $(k-1)(M+N)+1$ to $k(M+N)$, $k=1,\dots,K$. This matrix also can be written as:

$$C^{(k)}[n] = \mathcal{H}^{(k)}[n]B_k, \tag{4.22}$$

where the matrices $\mathcal{H}^{(k)}[n]$ and B_k are defined in the equations (4.7) and (4.11) respectively.

The delay matrix B_k is deterministic, has a known structure, and has a full row rank. Thus the propagation delay can be estimated using a non-linear LS criterion:

$$\begin{aligned} \hat{\tau_k} &= \arg\min_{\tau_k}\{J(\tau_k)\}; \qquad (4.23)\\ J(\tau_k) &= \sum_{n=N_{st}+1}^{N_{st}+S} \left(\mathbf{e}^{(k)}[n]^H \mathbf{e}^{(k)}[n]\right); \\ \mathbf{e}^{(k)}[n] &= \mathbf{x}[n] - \hat{C}^{(k)}[n]B_k^{\#}\mathbf{r}_{c,k}[n], \end{aligned}$$

where $(.)^{\#}$ is the pseudo-inverse operator, N_{st} is the time index when the channel estimation algorithm converges and S is the period for which we average the cost function $\mathcal{J}(\tau_k)$. The LS criterion was chosen because the available training sequence is limited. The cost function $J(\tau_k)$ is evaluated numerically, for all discrete delays over a certain grid in the interval $[0, M)$. The selected grid interval is a trade-off between the maximum acceptable delay estimation error and the computational complexity. A very small target for the delay estimation error results in an exhaustive search on the cost function $J(\tau_k)$. The delay estimator needs a training sequence $\mathbf{r}_{c,k}[n]$ computed from the transmitted training chips and propagation delays, as in Equation (4.5). The presented method estimates both the integer and fractional part of the delay even though the latter is not explicitly needed for data detection. However, the delay information may also be used for purposes other than data demodulation, such as mobile location estimation. This algorithm does not take into account valuable information from the channel matrix special structure. This information can be used to further simplify the delay estimation procedure. Some strategies for the estimation of the integer part of the propagation delay, based on the channel matrix structure, are introduced next.

The first p_k columns of the matrix $C^{(k)}[n]$ are zero. The corresponding columns of the estimate $\hat{C}^{(k)}[n]$ contain only the channel estimation error. Therefore, it is reasonable to assume that most of the energy in the matrix $\hat{C}^{(k)}[n]$ is contained in the columns from p_k+1 to p_k+N+1. For this purpose, we compute the Frobenius norm of the sub-matrices of the matrix $\hat{C}^{(k)}[n]$ obtained by taking $N+1$ consecutive columns. The index of the sub-matrix with the maximum norm gives an estimate of the propagation delay p_k:

$$\hat{p}_k = \arg\max_p \parallel \hat{C}^{(k)} W_N(p) \parallel_F, \tag{4.24}$$

where $W_N(p) = \begin{bmatrix}\mathbf{0}_{(N+1)\times p} & \mathbf{I}_{N+1} & \mathbf{0}_{(N+1)\times(M-p-1)}\end{bmatrix}^T$. The method has low complexity. However, it is highly influenced by the quality of the channel matrix estimate.

Another important observation is that due to the Sylvester structure of the matrices $\hat{C}_q^{(k)}[n]$, their diagonals contain either the linear combination of the channel taps and propagation delays or the channel estimation error only. A possible solution for the delay estimation is to find the diagonals of the matrices $\hat{C}_q^k[n]$ with the highest energy. Only the diagonals with N_c elements are considered, since the others only contain the channel estimation error. The energy of the m-th diagonal of the matrix $\hat{C}_q^k[n]$ is given by:

$$\epsilon_q^{(k)}(m) = \sum_{i=1}^{N_c} |\hat{c}_q^{(k)}(i, i+m-1)|^2, \quad m = 1, ..., M + L_h \tag{4.25}$$

Summing over all the Q antennas we obtain the total energy $\epsilon^{(k)}(m) = \sum_q \epsilon_q^{(k)}(m)$. The index corresponding to the first energy value which exceeds a given threshold is p_k+1. This method performance depends very much on the quality of the channel matrix estimate and the choice of the energy threshold. The threshold setting is performed experimentally. This threshold should be set so that it cannot be exceeded by energy terms which do not contain the channel taps. Simulation results in *Paper IV* show that a value of the threshold of 13dB more than the channel estimation error variance, which is also the minimum energy term, ensures good performance. The performance of the maximum energy method is degraded if the channels have little energy in the first tap (non-minimum phase).

The block diagonal of the product $\hat{C}[n]^H \hat{C}[n]$ is formed from K matrices of dimension $(M+N) \times (M+N)$, corresponding to each of the K users, given by:

$$D_k[n] = \sum_{q=1}^{Q} \hat{C}_q^{(k)H}[n] \hat{C}_q^{(k)}[n], \qquad k = 1, \ldots, K. \tag{4.26}$$

The structure of the matrices $C_q^{(k)}[n]$ is illustrated in Figure 4.1.

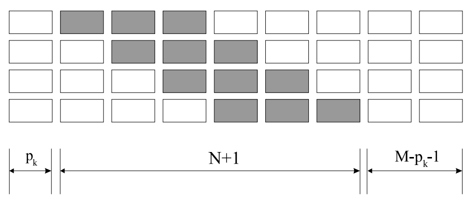

Figure 4.1: The structure of the $C_q^{(k)}[n]$ matrix where p_k is the integer part of the propagation delay, $N = N_c + L_h - 1$ and M is the maximum propagation delay. The filled rectangles represent non-zero elements while the white ones represent the zero elements.

If the channels are perfectly estimated, the diagonal of $D_k[n]$ has first p_k elements equal to 0, then the following $N+1$ elements are:

$$\Bigg[|c_q^{(k)}(0,n)|^2 \quad \sum_{i=0}^{1} |c_q^{(k)}(i, n-1+i)|^2 \quad \ldots \quad \sum_{i=0}^{L_h} |c_q^{(k)}(i, n-L_h+i)|^2 \quad \ldots \tag{4.27}$$
$$\sum_{i=0}^{L_h} |c_q^{(k)}(i, n-N_c+i+1)|^2 \quad \sum_{i=1}^{L_h} |c_q^{(k)}(i, n-N_c+i)|^2 \quad \ldots \quad |c_q^{(k)}(L_h, n-N_c+1)|^2 \Bigg],$$

and the last $M-p-1$ elements are also equal to zero. In a realistic scenario, only a noisy estimate of the channel matrix is available at the receiver. Therefore, there will be no zero elements on the diagonal of $D_k[n]$. If we take a closer look at the expression (4.27), we can observe that $(N_c - L_h)$ elements from $L_h + 1$ to N_c are equal to the sum of the squared absolute value of all the estimated channel taps at $L_h + 1$ consecutive time indexes. We assumed that the channels are slowly time-varying and therefore quasi-stationary over one symbol period. As a result, the non-zero elements in the rows of the matrices $C_q^{(k)}[n]$ change slowly over $L_h + 1$ chip periods. Consequently, the elements from index $L_h + 1$ to index N_c in (4.27) are almost equal and they approximate the channel norm at the time index $n - L_h$. The diagonal of the matrix $D_k[n]$, $\hat{\mathbf{v}}_k[n] = \text{diag}\{D_k[n]\}$, is called the estimated propagation delay profile of the k-th user. The estimate of the integer part of the delay is obtained by finding the $(N_c - L_h)$ largest consecutive values in the estimated propagation delay profile. We use a sliding window of length $S = N_c - L_h$ and we compute the power of the elements in the temporal window:

$$P_k(n) = \sum_{i=0}^{S-1} \hat{v}_k^2(n+i), \quad n = \{1, \ldots, M + 2L_h\}, \tag{4.28}$$

where $\hat{v}_k(n)$ are the components of the estimated propagation delay profile $\hat{\mathbf{v}}_k[n]$. The index of the maximum power value, $\max\{P_k(n)\}$, is at position $p_k + L_h$. Therefore, the integer part of the propagation delay, p_k, can be estimated if the maximum CIR length L_h is known.

If the adaptive channel estimator introduced in Section 4.1 is used, a limited number of channel matrix estimates are available. Therefore we can average the computation of the $\hat{\mathbf{v}}_k[n]$ over a temporal window of length T to reduce the effect of the channel estimation error. The simulation results in *Paper VIII* show that the averaging window length has to be chosen selectively, depending on the SNR. In high SNR (more than 5dB) cases no time averaging is needed while for low SNR the time averaging significantly improves the delay acquisition probability. The large sample properties of the delay profile method are investigated in *Paper VIII*. It is shown that the estimated propagation delay profile is a biased estimate of the true propagation delay profile. The bias term is positive and it is given by the variance of the channel matrix estimation error. The bias term is shown to have the same pattern as the true propagation delay profile.

The LS delay estimator proposed in *Paper V* estimates both integer and fractional part of the delay. Therefore the delay estimation error was considered as the appropriate performance measure. It is defined as $|\tau_k - \hat{\tau}_k|$. All the other methods deal with the estimation of the integer part of the delay. The correct acquisition of the integer part of the delay is crucial for the receiver performance. Consequently, the probability of correct acquisition is an appropriate measure of performance. It is defined as $Pr(p_k = \hat{p}_k)$ and it is practically evaluated over a large number of independent runs of the algorithms. In realistic scenarios none of the performance indicators cannot be used since the delays are not directly observable. More appropriate is the usage of the SER or BER at the receiver output. In *Paper VIII* the influence of the proposed delay estimators in the receiver SER performance is presented also.

The best performance is delivered by the delay profile method. The maximum norm method and maximum energy methods are more sensitive to the quality of the channel matrix estimate. The performance of the maximum energy method is in particularly sensitive to the setting of the energy threshold and to non-minimum phase channels. The LS delay estimator requires longer training sequence in order to achieve reliable performance.

The proposed delay estimation algorithms are summarized in Table 4.2.

LS delay estimation:	For each user $k = 1, \ldots, K$, for each $\tau_k = 0, \ldots, M-1$, given S consecutive channel estimate realizations $\hat{C}^{(k)}[n]$ Construct the delay matrices B_k and the transmitted data vectors $\mathbf{r}_{c,k}[n]$ using the training data. Collect the received data in the vectors $\mathbf{x}[n]$ $\mathbf{e}^{(k)}[n] = \mathbf{x}[n] - \hat{C}^{(k)}[n] B_k^{\#} \mathbf{r}_{c,k}[n]$ $J(\tau_k) = \sum_{n=N_{st}+1}^{N_{st}+S} \left(\mathbf{e}^{(k)}[n]^H \mathbf{e}^{(k)}[n]\right)$ $\hat{\tau_k} = \arg\min_{\tau_k} \{J(\tau_k)\}$
Maximum norm method	For each user $k = 1, \ldots, K$, given and estimate $\hat{C}^{(k)}[n]$, for $p = 0, \ldots, M-1$ $W_N(p) = \left[\mathbf{0}_{(N+1)\times p} \;\; \mathbf{I}_{N+1} \;\; \mathbf{0}_{(N+1)\times(M-p-1)}\right]^T$ $\hat{p}_k = \arg\max_p \parallel \hat{C}^{(k)} W_N(p) \parallel_F$
Maximum energy method	For each user $k = 1, \ldots, K$, given the estimates $\hat{C}_q^{(k)}[n]$, $q = 1, \ldots, Q$ $\epsilon_q^{(k)}(m) = \sum_{i=1}^{N_c} \lvert\hat{c}_q^{(k)}(i, i+m-1)\rvert^2, \quad m = 1, ..., M + L_h$ $\hat{p_k} = \arg\min_m (\sum_q \epsilon_q^{(k)}(m)) - 1$
Delay profile method	Given S consecutive realizations of $\hat{C}[n]$ $\mathcal{C} = \frac{1}{N_{st}} \sum_{n=1+N_{st}}^{S+N_{st}} \hat{C}^H[n] \hat{C}[n]$ $\hat{\mathbf{v}} = \mathrm{diag}\{\mathcal{C}\}$ $\hat{\mathbf{v}}_k = \hat{\mathbf{v}}\left[(k-1)(M+N)+1 : k(M+N)\right]$ $k = 1, \ldots, K$ Select a sliding window of length $S_1 = N_c - L_h$ and compute: $P_k(m) = \sum_{i=0}^{S_1-1} \hat{v}_k^2(m+i)$ $m = 1, \ldots, M + 2L_h$ $\hat{p}_k = \arg\max_m (P_k(m)) - L_h$.

Table 4.2: The pseudo-code of the proposed delay estimation algorithms

4.3 Discussion

In this chapter a novel receiver structure for long-code DS-CDMA is introduced. An uplink scenario is considered, with several active users transmitting their signals to a BS equipped with multiple antennas. The resulting multi-user system is characterized by a channel matrix which includes the CIR's corresponding to each user as well as the propagation delays. Therefore, estimating this matrix leads to an implicit estimation of the CIRs and propagation delays. An adaptive multi-user stochastic gradient channel estimation method is proposed. It enables better tracking of the time-variations of the channels since a modeling of the channels' temporal evolution is included in the algorithm derivation.

It could be argued that the channel modeling is not very accurate since it does not including specific channel parameters such as the Doppler spread. However, it is very difficult (if not impossible) to accommodate an accurate channel model in the algorithm derivation. The dynamics of each parameter which characterizes the channel are different. Moreover, the parameters depend on the propagation environment. The minimization of the MSE, which is the objective function of the algorithm, will be performed in this case with respect to a large number of parameters which increases the algorithm complexity. A more general and simplistic channel model is used in order to keep the algorithm complexity at reasonable levels. Similar channel modeling has been used in the literature [67, 170, 78]. The modeling parameters could be selected based on the channel models (terminal speed, delay profile etc.) [114, 115, 116, 117]. A simple, and perhaps less accurate channel modeling is still better than no modeling. This statement can be easily verified in the simulations presented in *Paper VI*, where the proposed channel estimator performance is superior to that of an algorithm which does not consider any channel model at all. The channel estimator is tested in simulation with realistic channel models [58]. The algorithm needs a relatively short training sequence (about 30 symbols) to converge and exhibits good channel tracking capabilities. The price to be paid for simplistic channel modeling is that the algorithm may be applied only in low to medium mobile speed scenarios. If the mobile station speed increases , the channel estimator may lose the track and therefore more frequent training of the algorithm is required. This decreases the effective data rate of the link. In high speed applications more training is needed or more powerful tracking mode receivers with more accurate channel models are needed and thus with increased complexity.

The algorithm convergence and tracking performance depend on the selection of two step-size parameters. For the first step-size parameter Δ the range of values is provided for which the channel estimator convergence is ensured. An optimal fixed value of the step-size parameter Δ is also computed by assuming that the excess error is not and increasing function in time. The second step-size parameter Δ_1 is much more difficult to analyze. Its range of values is established experimentally and it depends on the channel dynamics. However, the algorithm behavior is not very sensitive to this parameter choice. Simulation results in *Paper VI* show that there is a large range in the step-size parameter Δ_1 for which the channel estimator performance is similar. The step-size choice is dependent on the channel's dynamics, its value increasing with the channel maximum Doppler spread.

The multi-channel estimators perform well for moderate near-far effects (less than 10dB NFR). It is shown in simulations presented in Paper VI that its convergence speed depends on the near-far ratio. Therefore algorithm training has to be done adaptively for each user taking into account its received power level. If its received signal is very weak compared to the other users, longer training is needed.

The most computationally demanding part of the proposed receiver algorithm is the MMSE equalizer. It involves inversion of a matrix of the size $QN_c \times QN_c$ at each sampling time instance. Therefore, for a large number of receive antennas, or very high spreading factors (low date rate), the computational complexity increases significantly. However, the computations are performed at the BS, where adequate computational power is often available. Moreover, efficient numerical algorithms may be used to reduce the computational complexity. The MMSE equalizer is used for performance analysis purposes only. The channel estimates can be used in other data demodulation strategies such as interference cancellation methods. The MMSE equalizer is used because it is a straightforward solution, once the channel matrix estimate $\hat{C}[n]$ is available.

The propagation delay estimation problem is significantly simplified since only the integer part of the delay is needed for reliable data demodulation. The strategies based on the channel matrix structure deliver a high acquisition probability, even in very low SNR scenarios with unequal received powers. Their performance depends on the quality of the channel matrix estimates.

The proposed channel estimator needs training symbols, unlike blind methods [82, 200, 207]. Therefore the effective data rate is smaller. In fact, some training/pilot symbols are always needed in practical wireless systems, especially for high mobility links. The proposed algorithm is able to track the time variations of the channels whereas the blind methods are derived from assumptions about stationary conditions. Most of the channel estimators proposed in the literature, blind or trained, are based on this assumption. Channel tracking methods [67, 92, 205] are an exception. These methods are very sensitive to the initial delay acquisition and have a higher degree of computational complexity. The problem of delay tracking is not considered in the proposed algorithm. However, the proposed acquisition methods may be extended to perform the delay tracking or they can be used as an initial stage in a tacking mode receiver.

The literature regarding the long-code asynchronous DS-CDMA receiver structures is very limited. The main contribution of this thesis is that a complete receiver structure is proposed. The receiver consists of three parts connected to a compact solution: a channel estimator, an equalizer and a delay estimator. The receiver delivers reliable data detection for all the active users simultaneously. In uplink, this is a desirable behavior, since a user-by-user sequential demodulation requires temporary data storage, or buffering, for each active user signal.

Chapter 5

Channel estimation and time synchronization in OFDM systems

OFDM is proposed by Chang in his pioneering work of [24]. The main idea behind OFDM is to divide the frequency selective channel into a number of parallel, frequency flat sub-channels. Since its discovery, this technique has fascinated researchers but due to implementation complexity it has only recently found applications with which it can be used. The new European digital audio broadcasting (DAB) and terrestrial television broadcast (DVB-T) standards adopted OFDM. WLAN standards HiperLAN and IEEE 802.11, as well as the asymmetric digital subscriber loop (ADSL) are major applications that use OFDM for high data rate transfer. An excellent overview of OFDM receivers for WLAN can be found in [56]. OFDM is also proposed for multiuser systems such as Universal Mobile Telecommunication System (UMTS) [48]. It is also considered in beyond third generation and fourth generation mobile wireless systems.

The OFDM spectrum, divided along many orthogonal sub-carriers is illustrated in Figure 5.1. Assuming correct sampling, the sub-carriers are orthogonal even though they overlap. Therefore there is no interference between the signals modulated on adjacent sub-carriers. In order to preserve their orthogonality the carrier frequencies have to be accurately known at the receiver. Any mismatch between the receiver and transmitter carrier frequency (carrier frequency offset) causes inter-carrier-interference and it is a ma-

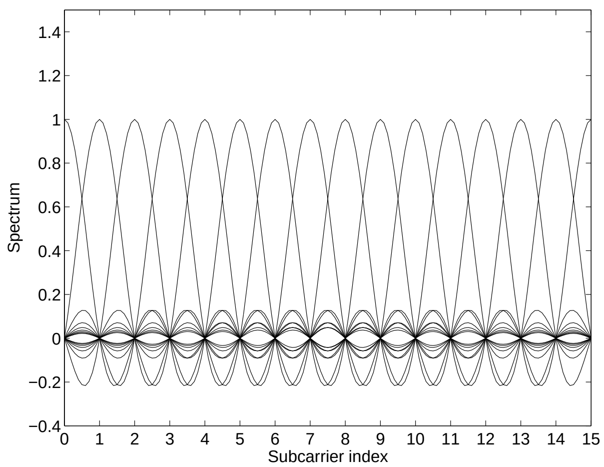

Figure 5.1: The OFDM transmission spectrum

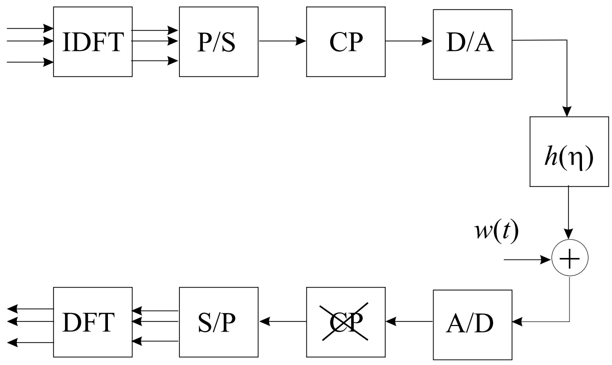

Figure 5.2: The baseband model of the OFDM system considered in the thesis.

jor source of performance loss in any OFDM system. The frequency offset may also be due to the Doppler effect in the mobile communications channels. The time synchronization also plays a very important role in OFDM system design. Sufficiently large time synchronization error causes severe inter-block-interference (IBI). Unlike the single carrier systems, OFDM is more sensitive to synchronization errors than to transmission channel impairment (inter-symbol-interference).

In this chapter, the problems of channel estimation and time synchronization in OFDM transmission are considered. Fixed wireless links are assumed with packet transmission. This corresponds to the WLAN system model [2], for example. The most important methods for channel and delay estimation proposed in the literature are reviewed. The author contributions to this problem are presented in subsection 5.4. Many aspects regarding OFDM transceivers, such as frequency synchronization and the peak power problem, are not presented here since they are beyond the scope of this thesis. Excellent treatment of many problems encountered when designing OFDM systems can be found in [178, 194].

5.1 OFDM system model

A block diagram of the baseband model for an OFDM link is depicted in Figure 5.2. We consider a single user scenario in a fixed wireless network. It is assumed that a high data rate information bits stream $u(m)$, drawn from a QAM constellation, is transmitted. The serial data stream is converted to M parallel data streams:

$$\mathbf{u}[n] = \left[u((n-1)M+1), u((n-1)M+2), \ldots, u(nM)\right]^T. \tag{5.1}$$

The parallel data stream $\mathbf{u}[n]$ is modulated on M orthogonal sub-carriers using an Inverse Discrete Fourier Transform (IDFT). This operation can be performed with a computationally efficient fast Fourier transform (FFT) algorithm. Then, the parallel data stream is converted to serial. At the receiver, each OFDM block is affected by the previous block due to the transmission channel. In order to avoid IBI, a cyclic prefix (CP) is added at the beginning of each OFDM block, by copying the last P samples from the block. The length of the CP has to be larger than the CIR delay spread. The modulation and CP adding operations can conveniently be represented in matrix form as follows:

$$\begin{aligned}
\mathbf{s}[n] &= \mathbf{TFu}[n] \qquad (5.2)\\
\mathbf{T} &= \begin{bmatrix} \mathbf{0}_{P\times(M-P)} & \mathbf{I}_P \\ \mathbf{I}_{(M-P)} & \mathbf{0}_{(M-P)\times P} \\ \mathbf{0}_{P\times(M-P)} & \mathbf{I}_P \end{bmatrix}\\
\{\mathbf{F}\}_{gq} &= \frac{1}{\sqrt{M}} e^{j\frac{2\pi gq}{M}}, \quad g,q \in \{0,\ldots,M-1\},
\end{aligned}$$

where $\mathbf{T}$ is the $(M+P)\times M$ matrix which performs the cyclic prefix addition and $\mathbf{F}$ is the $M\times M$ IDFT matrix. The resulted sequence is converted to analog, modulated on a carrier with frequency ω_c and send through a channel with the CIR $h(\eta)$. At the receiver a conventional IQ-mixing stage is used similar to that presented in Figure 3.5. The CP is discarded and therefore the IBI is eliminated assuming that the CP length has been correctly chosen. The received signal sampled at the data symbol rate may be written as:

$$y(m) = h(m) * s(m-\delta)e^{j2\pi\epsilon m/N} + w(m), \qquad (5.3)$$

where the operator $*$ denotes the convolution sum, δ is the time offset between the transmitter and the receiver, ϵ is the carrier frequency offset between the transmitter and the receiver and $w(m)$ are additive noise samples assumed i.i.d. Gaussian distributed with zero mean and known variance. Since fixed wireless links are considered, the channels are assumed to be time invariant over the observation interval. If the receiver and the transmitter are perfectly synchronized in time (the receiver knows the time instance when the transmission started), the CP in the received signal is dropped. Then, the serial stream is converted back to M parallel streams and a DFT operation is applied in order to demodulate the original data. The resulting data stream is multiplied by the channel frequency response (CFR). Therefore, the equalization may be performed in a simple manner in the frequency domain with the inverse of the CFR, i.e. zero forcing (ZF) equalization. Alternatively to the ZF equalization, a MMSE solution can be used as well.

Another option to eliminate the IBI is to add zeroes at the end/beginning of the OFDM block. This procedure is called zero-padding (ZP). At the receiver, the samples corresponding to the zeroes are dropped. Hence the IBI is eliminated. However, only the CP transforms the linear convolution of the signal with the channel in a cyclic convolution. After the DFT at the receiver, the data modulated on sub-carriers are multiplied with the corresponding complex CFR. The channel estimation is hence a necessary step in a coherent OFDM receiver. It may be avoided completely by using a differential encoding on the transmitted data, and employing a non-coherent OFDM receiver. This approach results in an SNR loss of 3dB at the receiver [178].

In realistic scenarios, the time delay between the transmission and reception has to be estimated in order to properly discard the CP and apply the DFT temporal window. If the delay is smaller than the length of the CP, there is no loss in performance due to the cyclic properties of the DFT. If the delay is larger than the CP, then the loss in performance is significant. This is due to the fact that in the current DFT window samples from the neighboring OFDM blocks are processed together with the samples from the desired OFDM block. Even small delay offsets (less than the sampling period) cause a drastic loss of performance. Therefore, special attention has to be paid to time synchronization problem when designing an OFDM receiver.

5.2 Channel and delay estimation in OFDM

5.2.1 Channel estimation

All the useful signal characteristics have to be taken advantage of when designing a receiver for wireless communications. General algorithms may be simplified when applied to a particular problem. In OFDM, the signal structure with redundancy introduced by the CP is often exploited. The usage of pilot signals on special sub-carriers also allows for improvements in receiver performance without wasting whole available spectrum.

After the DFT operation at the receiver and assuming that perfect time and frequency synchronization is performed, the baseband signal can be written as:

$$Y(n,k) = H(n,k)u(n,k) + W(n,k), \tag{5.4}$$

where n is the OFDM symbol index, k is the sub-carrier index, $H(n,k)$ is the channel frequency response, $Y(n,k)$ is the received sequence in frequency domain, $u(n,k)$ is the transmitted data sequence and $W(n,k)$ is the noise component in frequency domain. Therefore, if the CFR is well estimated the equalization is easily performed by multiplying the received data on each sub-carrier with the inverse of the corresponding CFR.

Non-coherent data demodulation based on differential encoding can be used as an alternative. Such an approach has the advantage that the channel estimation is not needed. However, a loss of 3dB in SNR is experienced when compared to coherent demodulation. Moreover, the coherent demodulation achieves a better performance for higher order constellations than those used with non-coherent demodulation [178]. Therefore, the coherent demodulation is preferable for high data rate applications, which are of interest in this thesis.

In this subsection channel estimation methods for OFDM proposed in the literature are reviewed. Frequency domain approaches are introduced first. Several strategies using pilot symbols on certain sub-carriers are presented. Time-domain channel estimation methods are also addressed. The problem of channel estimation in multi-user OFDM systems is considered and blind channel estimation algorithms are briefly presented.

Pilot symbols based channel estimation in frequency domain

One solution for the channel estimation in OFDM is to transmit known pilot symbols on certain sub-carriers [57, 89, 87]. Denoting the pilot sub-carrier frequencies index set with $\mathcal{P}$ and assuming that the symbols are drawn from a PSK constellation, the channel is estimated using the following scheme:

$$\tilde{H}(n,k') = Y(n,k')u^*(n,k') = H(n,k') + W(n,k')u^*(n,k'), \quad k' \in \mathcal{P}. \tag{5.5}$$

The CFR at the data bearing sub-carriers are estimated by interpolating $\tilde{H}(n,k')$ in the frequency domain or in the time domain, or both.

Hoeher et al. derive in [59] the two-dimensional time-frequency Wiener filter. The estimator assumes knowledge of the double selective channel statistics, a condition which is hard to fulfill in realistic scenarios where the channel is not directly observable. Li et all. propose in [89] an optimum MMSE channel estimator based on pilots. The estimator makes full use of the double selective channel correlations in both the time and frequency domains. Therefore the optimum MMSE estimator can only be found when the channel's statistics are known. A more realistic case where the channel's statistics mismatch is also considered. It is proved that the loss in performance is acceptable if the channel correlations match the Doppler spectrum [89].

An optimum MMSE interpolator applied after the CFR estimation at the pilot frequencies is proposed in [87]. As the optimum MMSE channel estimator, the existence of the optimum MMSE interpolator is also dependent on the knowledge of the channel statistics. However, the interpolator can be less sensitive to the channel statistics with a properly chosen filtering shape. An orthogonal coding pilot scheme for the channel estimation is introduced in [57]. The data symbols are coded using a code with higher rate c_1 while the pilot symbols are coded using a code c_2 orthogonal to c_1. At the receiver the sampled signal is filtered with a filter matched to the pilot code, delivering a noisy estimate of the CFR.

If the channel is assumed to be stationary during an OFDM symbol, the equation (5.4) can be written in matrix form taking into consideration the data, CFR and noise at all sub-carrier frequencies:

$$\mathbf{Y} = \mathbf{UH} + \mathbf{W}, \tag{5.6}$$

where $\mathbf{U}$ is a diagonal matrix containing the data transmitted during an OFDM symbol. In [34] a linear MMSE (LMMSE) channel estimator is proposed using the above system model. Given knowledge of the transmitted data on all sub-carriers, a least square channel estimate is obtained $\hat{\mathbf{H}}_{LS} = \mathbf{U}^{-1}\mathbf{Y}$. The final LMMSE channel estimate is given by:

$$\hat{\mathbf{H}}_{LMMSE} = \mathbf{R}_{hh}(\mathbf{R}_{hh} + \sigma_w^2(\mathbf{U}\mathbf{U}^H)^{-1})^{-1}\hat{\mathbf{H}}_{LS}, \tag{5.7}$$

where $\mathbf{R}_{hh} = E[\mathbf{H}\mathbf{H}^H]$ is the channel correlation matrix. Channel estimator complexity is simplified by using a low rank approximation of the channel. It is observed in the simulations that the approximation of the channel statistics with a uniform power-delay profile keeps the performance degradation at an acceptable level. A DD method for channel estimation is proposed in [107]. Starting with known pilots in the first OFDM symbol, the algorithm uses the decisions from the receiver which are then improved by using a correction code to estimate the CFR in the next frames. The method assumes the time invariance of the channel for at least 2 OFDM symbols. Time and frequency domain filtering is also applied to reduce the estimation error effect. For frequency selective channels, the reliability of the channel estimate at each sub-carrier is taken into account when performing the error-correction decoding.

One important issue is the number of pilot symbols used for channel estimation as well as their optimal placement. This problem is critical, especially for time-varying channels. In [33] the optimal placement of the pilots is considered when a Kalman filter is used to track the channels in the frequency domain. It is proved in this paper that sending few pilot symbols more frequently is better than sending a larger number of pilot symbols less frequently.

Pilot symbols based channel estimation in time domain

The channel estimation methods presented so far process the data in the frequency domain after the DFT at the receiver. The estimate of the CFR contains errors, therefore for reliable data detection it is preferable to refine it. If an IDFT is applied again on the CFR, the resulting CIR has the length M. Usually this is an over-estimated channel order since a large number of taps have very little energy. The noise in these channel taps has a higher power than the multipath energy contained in them. The channel estimation performance can be improved by estimating the channel order and neglecting the low energy taps. After the tap selection operation, the shortened CIR is passed again in the frequency domain and used for equalization. The performance of different strategies for channel tap selection is discussed in [108].

A time domain LS channel estimation method is proposed in [56] (page 79), when entire OFDM training symbols are available. The received time domain samples corresponding to the training symbol after CP removal can be written as:

$$\mathbf{r}_t[n] = \mathbf{X}_c[n]\mathbf{h} + \mathbf{w}[n], \tag{5.8}$$

where $\mathbf{X}_c[n]$ is the circular convolution matrix of size $(M \times L_h)$ formed from the training data and $\mathbf{h}$ is the channel impulse response of size L_h. Therefore the CIR can be estimated as:

$$\hat{\mathbf{h}} = \mathbf{X}_c^{\#}[n]\mathbf{r}_t[n], \tag{5.9}$$

where the operator $(.)^{\#}$ stands for the Moore-Penrose generalized inverse. The performance of the estimator is further improved if two consecutive and equal training symbols are available (IEEE 802.11 standard). This reduces the influence of the additive noise. The CFR is computed based on the estimated CIR. In practice, the number of sub-carriers is higher than the order of the CIR. The time domain channel estimation gives better results than the CFR estimation since a smaller number of parameters are estimated using the same data.

A time-domain channel estimation and tracking method for mobile OFDM communications is proposed in [141]. Starting with a state-space description of the system model, a Kalman filter is employed for the time-varying CIR acquisition and tracking. A training sequence is employed at the beginning of the transmission for initial channel acquisition. The channel tracking is performed using the data decisions in a DD manner. The algorithm is extended to MIMO systems [142] as well as the estimation of the frequency offsets [140].

Transmit diversity

Transmitter diversity is an effective technique for improving the performance of wireless communications. The resulting systems are multiple-input-single-output (MISO) or MIMO systems, depending on the receiver configuration. Space-time coding is studied with OFDM modulation in [5]. Even though the increase in system capacity is high compared to single antenna systems, the decoding of the space-time codes requires knowledge of the channel state. Using training symbols at the beginning of the transmissions, Li et. al [90] propose a time domain method for channel estimation for transmit diversity schemes with 2 receive and 2 transmit antennas. The complexity of the CIR estimator is furthermore simplified by selecting only the channel taps with the highest energy, at the cost of small performance loss. With a proper design for the training symbols, the channel estimator is further simplified [88]. The algorithm is difficult to use in DD mode since the special training symbols are only available at the beginning of the transmission. A simplified channel estimator is also proposed in the case of normal training symbols. The robust channel estimator in [89] computed at the OFDM symbol index $n-1$ is used to estimate the CIR at the symbol index n. An enhanced channel estimator for a more general $4 \times p(p \geq 4)$ MIMO system is developed in [91]. The delay profiles of the channels can be used to further increase the channel estimator performance. The enhanced channel estimator is used in conjunction with a pre-whitening processing to deliver performance levels close to the ideal case if the Doppler spread of the channels is less than 100Hz.

Blind channel estimation

It can be observed that in the methods presented so far, a significant part of the available spectrum is used for transmission of the pilot symbols, which reduces the effective data rates of the system . Therefore, blind channel estimation methods are of great interest. Many blind channel estimators have been developed for OFDM. Some of them are related to multi-carrier systems without CP [28], while others are based on cyclostationarity [71] and subspace decompositions that exploit the CP or ZP structure of OFDM transmissions [146].

In [17] a non-constant modulus precoding scheme is proposed for blind identification and equalization of an OFDM-CP-based MIMO system using SOCS. The cyclostationarity is induced by periodical precoding at the transmitter [70, 146, 211], with different signatures in the cyclostationary domain for each transmit antenna. The redundancy introduced by CP is used to identify each sub-channel individually. The transmitted symbols are recovered up to a phase rotation (a diagonal matrix of phase terms). This remaining complex scale ambiguity can be solved using short training sequences. The transmitter redundancy using filterbank precoders [147] generalizes existing modulation schemes including OFDM and CDMA. A sufficient number of conditions are derived to guarantee that with the use of FIR filterbank precoders the FIR channels are equalized perfectly in the absence of noise, irrespective of channel zero-location [147].

Methods relying on the finite alphabet property of information bearing symbols are also proposed. These methods are applicable to both CP- and ZP-OFDM transmissions. PSK transmissions with the method proposed in [210] enable channel estimation even from a single OFDM block at high SNR, which is something that can not be achieved by statistical methods such as [71]. Reducing the required sample size even allows the tracking of fast channel variations. Furthermore, by exploiting the finite alphabet property, the scalar ambiguity inherent to all blind algorithms is restricted so that it has unit amplitude and phase values belonging to a finite set, one which can be easily resolved. In [7] a subspace method for blind channel estimation is developed for a CP-free OFDM system. The idea is to oversample the channel output in the spatial domain by using multiple antennas and estimating the channel based on second order statistics of the received signal. The channel estimator takes into account known zeroes inserted at the end of the OFDM data block, which corresponds in the frequency domain to un-modulated (virtual) sub-carriers [15, 83] in the roll-off region. If no data is transmitted on a sub-carrier, it is called a virtual sub-carrier.

Remarks

Coherent demodulation is needed for high data rate transmissions. Therefore, the channel estimation has to be performed at the receiver.

Since the CFR is used for equalization, most of the methods are pilot-aided in frequency domain. The main advantages of these methods is the low complexity and easy implementation. They require additional processing to estimate the CFR on the sub-carriers other than the pilot ones. These methods are very sensitive to fading channels. If deep fades occur in the CFR at the pilot frequencies, then the channel estimation may be compromised. Their applicability is restricted to fixed wireless scenarios. Moreover, in high mobility scenarios the channels tracking may be needed. In frequency domain, this means the tracking of a large number of parameters. Therefore, the complexity of the channel estimators may significantly increase. On the other hand, the CIR has in general less number of parameters than the CFR. Therefore, the channel tracking in time domain is preferable. The time domain channel estimation has received little attention in the literature. These techniques have usually higher complexity than the frequency domain approaches. They require the knowledge of training data on all sub-carriers for a certain time period. Instead, they do not require any post-processing. Some of the actual

	Frequency domain [59, 89, 57]	**Time domain** [56, 141]	**Blind methods** [28, 71, 70, 146]
Training data	Training symbols on pilot sub-carriers	Training symbols on all sub-carriers	No training
Complexity	Low, post-processing needed	Higher than freq. domain methods	Higher than the others
Performance	Sensitive in fast fading channels, channels statistics required	Robust in fast fading channels	Robust but remaining ambiguities
Channel cond.	Freq. selective fading	Freq. selective fading	Freq. selective time invariant

Table 5.1: Comparison of frequency domain and time domain channel estimation for OFDM

standards [2] allows for time-domain channel estimation since special OFDM blocks are allocated in this purpose.

Blind channel estimation techniques are especially suitable for fixed wireless communications. In order to solve the remaining ambiguity problems, some training may be required.

A comparison of the main approaches for channel estimation in OFDM is summarized in Table 5.1.

5.2.2 Time synchronization techniques

The channel estimation methods discussed in the previous subsection usually assume a perfectly synchronized system. In this section several time synchronization strategies are discussed. Many of them are based on the redundancy introduced into the OFDM signal by the CP. ML estimators are derived based solely on the CP or by also using pilot symbols. Blind synchronization based on the cyclostationarity of the received signal of the pulse-shaped OFDM is considered as well. The usage of virtual sub-carriers for synchronization purposes is also presented.

ML synchronization methods

Van de Beek et al propose [177] an ML method for time delay estimation in flat fading channels that exploits the CP without the need for any pilots. The time delay is assumed to be less than the OFDM symbol length. Therefore, the received signal samples are stacked in a $2M + P$ samples vector $\mathbf{y}$. Under the assumption that this vector is jointly

Gaussian and that the frequency offset is known or has been estimated, the log-likelihood function of the time offset can be expressed as::

$$\begin{aligned}
\Lambda_{CP}(\delta) &= |\gamma(\delta)| - \rho\theta(\delta) \qquad (5.10)\\
\gamma(m) &= \sum_{k=1}^{m+P-1} y(k)y^*(k+M)\\
\rho &= \frac{\sigma_u^2}{\sigma_u^2+\sigma_w^2}\\
\theta(m) &= \frac{1}{2}\sum_{k=m}^{m+P-1} |y(k)|^2 + |y(k+N)|^2,
\end{aligned}$$

where σ_u^2 is the transmitted signal power and σ_w^2 is the additive noise variance. The term $\gamma(m)$ is the sum of P consecutive correlations between pairs of samples spaced M samples apart. The term $\theta(m)$ is an energy term and ρ is a weighting factor dependent on the SNR. The log-likelihood function is evaluated at all the positive integer values smaller than M. The estimate of the delay δ is the argument which maximizes this function. The algorithm performance is influenced by the length of the cyclic prefix and the noise level. The method performs well for frequency flat channels but exhibits an error floor for frequency selective channels since the CP samples contain interference from the previous OFDM block. A solution that mitigates this problem is proposed in [64] where different smoothing algorithms replace the moving average sum in (5.10). The modified methods are shown in simulations to outperform the original synchronization method in frequency selective channels.

In an OFDM system there will always be pilot signals used for synchronization and channel estimation purposes. Consequently, the performance of the timing estimators can be enhanced. Landström et al propose [79] an improved ML timing estimator using both CP and training pilots. Two log-likelihood functions of the time delay are constructed by also considering the contribution of the pilot symbols. One log-likelihood function gives the position of the CP, thus giving an unambiguous but coarse timing estimate. Another log-likelihood function is a matched filter to the pilot symbols and this has many distinct correlation peaks that give an ambiguous estimate of the time delay. The weighted criterion combining the two functions yields an unambiguous and distinct peak of the log-likelihood function. The frequency offset causes an increase in the time delay estimator variance due to a random phase in the correlation sums. In order to avoid this problem, the absolute value is taken in the log-likelihood function thus preserving the constructive contributions of the peaks in the weighted log-likelihood function.

The ML estimator of [177] is extended to a multi-user OFDM transmission in [176]. The method is suitable for the uplink of the UMTS OFDM, as is proposed in [48], where a TDMA/FDMA multiple access scheme is considered. The available spectrum is subdivided into sub-bands of adjacent sub-carriers. Within each sub-band the user transmissions are separated in time. This multi-access scheme is very sensitive to synchronization errors. On each sub-band an OFDM symbol is transmitted with a specific CP. Therefore, at each time instance the receiver has to distinguish between several users allocated to each sub-band. The ML time delay estimator in [177] is applied on each sub-band. The performance of the delay estimator is influenced by the number of sub-carriers on each sub-band. It is desirable to have as many sub-carriers as possible on each sub-band, but on the other hand this means that fewer users can be accommodated. The delay estimator is modified in order to be able to also track time variations of the delay, by filtering the statistics with a one-pole IIR filter:

$$\begin{aligned}\bar{\gamma}_t(\delta) &= \alpha\bar{\gamma}_{t-1}(\delta) + (1-\alpha)\gamma_t(\delta) \\ \bar{\theta}_t(\delta) &= \alpha\bar{\theta}_{t-1}(\delta) + (1-\alpha)\theta_t(\delta),\end{aligned} \tag{5.11}$$

where $0 < \alpha < 1$ is a forgetting factor and $\gamma_t(\delta)$ and $\theta_t(\delta)$ are the one-shot statistics computed as in (5.10). Based on the filtered statistics the ML estimator is defined as:

$$\hat{\delta}_t = \arg\max_{\delta} \left\{ |\bar{\gamma}_t(\delta)| - \rho\bar{\theta}_t(\delta) \right\}. \tag{5.12}$$

Correlation based methods

The time synchronization problem for slotted OFDM transmissions in an ALOHA environment is studied by Warner and Leung in [195]. Unlike continuous transmissions, the ALOHA environment requires special treatment of the time synchronization: each OFDM frame has to be synchronized independently and the bandwidth overhead should be small. The synchronization method is a 3 step procedure. A power detection step is used first in order to detect a rough start in the transmission by measuring the received signal energy. In the second phase, a coarse delay acquisition is performed by correlating the received data with known pilot symbols in the frequency domain. The output of the correlator is passed through a digital interpolator with a higher sampling frequency which reduces the possibility of missing the correlation peak. In the third phase, the algorithm computes the time shift that maximizes the correlation of the received data after equalization with the reference synchronization signal. The required phase shift for each sub-carrier is then computed and applied prior to extracting the information symbols. The simulation results show a loss of 1.5 dB in performance when compared with ideal synchronization. The method needs a bandwidth overhead of 10% for synchronization.

In the method in [195] the pilot symbols are not specially designed. Schmidl and Cox consider in [148] a synchronization algorithm where specially designed pilot symbols are transmitted. The special OFDM block consists of two identical halves in time domain generated by transmitting a pseudo-random sequence on even frequencies and zeroes on the odd frequencies. In order to maintain a relative constant energy over the OFDM block, the training symbols are drawn from a larger power constellation than the transmitted data. At the receiver the algorithm tries to detect the two equal halves by computing the following metric:

$$\begin{aligned}\mathcal{M}(d) &= \frac{|\mathcal{P}(d)|^2}{R^2(d)} \\ \mathcal{P}(d) &= \sum_{m=0}^{M/2-1} y^*(m+d)y(m+d+M/2) \\ R(d) &= \sum_{m=0}^{M/2-1} |y(m+d+P)|^2.\end{aligned} \tag{5.13}$$

The metric $\mathcal{M}(d)$ reaches a maximum plateau which has the length of the CP minus the length of the channel impulse response, since there is no IBI within this plateau to distort the signal. An extension of this method to MIMO systems is proposed in [109]. In addition to this method, a fine time acquisition is also proposed based on the cross-correlation of the received data with known pilot symbols.

In [75] a reference symbol is proposed and a range of correlation based techniques are suggested for coarse and fine synchronization. A special structure for an OFDM multiple access scheme is proposed, and within this scheme there are three periodic time-domain structures exploited by the correlation based delay estimators. The technique's performance is studied in time-dispersive Rayleigh fading channels.

Blind time synchronization

Bölcskei proposes in [16] a blind method for synchronization in a pulse-shaped OFDM. The method exploits the CS introduced by the pulse-shaping operation to blindly identify both the symbol timing and the frequency offset. The pulse shaped OFDM is preferable for high data rate services since it reduces out-of-band emission and it has a reduced sensitivity to frequency offsets. Different ways of inducing cyclostationarity in the OFDM signal are discussed, including the carrier weighting (transmitting different sub-carriers with different powers). If no pulse-shaping and carrier weighting is performed, the OFDM signal is stationary and the blind synchronization cannot be performed based on the second order statistics. The proposed blind method does not need any CP to perform the synchronization. The blind delay estimators are based on the second order received signal CS statistics . The acquisition range is one OFDM block, but it can be extended by using a periodic non-constant weighting of the sub-carriers. Additional synchronization methods based on the cyclic spectrum of the received signal are also proposed. The methods are initially proposed for frequency flat channels. The influence of unknown time-dispersive channels is considered in simulations. The performance loss is significant compared with the frequency flat channels case.

A blind and channel independent method for OFDM synchronization is proposed in [8] for multi-user systems. A specific frequency assignment scheme is considered to achieve maximum separation among the frequencies that correspond to each user. The main idea behind the synchronization algorithm is to use virtual sub-carriers on which no data is modulated. In the time synchronous case, the frequency offset can be estimated based on the minimization of the energy on the virtual sub-carriers. In the asynchronous case the algorithm reduces to a two dimensional energy cost function minimization. This cost function has many local minima which may lead to an ambiguous delay estimation. The joint estimation of the time and frequency offsets can be split into two minimization problems if initial rough estimates of the delay and frequency offsets are available. The algorithm converges to the global minimum if the initial time delay is less than an OFDM symbol and the frequency offset less than $\frac{1}{2M}$.

Other methods

A joint channel impulse response and symbol timing estimator is proposed by Larsson et al in [80]. A coarse initial acquisition of the timing is assumed and the channel impulse response of length M is estimated based on an LS criterion. The estimated channel impulse response contains zero leading elements due to the timing error as well as zero padding elements due to the CIR order overestimation. An iterative technique is proposed to refine the time estimate using an LS criterion and to estimate the CIR length using the generalized Akaike information criterion. The channel length is usually underestimated in the simulation results since the last elements of the CIR are usually very weak. The proposed time synchronization method is only able to estimate integer time offsets.

	ML [177, 64, 79]	**Correlation** [195, 148, 75]	**Blind synchronization** [16, 8]
Side info	No training required, exploits the CP	Specially designed OFDM block	Pulse-shaping or virtual sub-carriers
Performance	Poor in frequency selective channels	Robust in freq. selective channels	Significantly degraded in frequency selective channels
Complexity	Low	Low	High
Channel cond.	Freq. flat fading	Freq. selective fading	Freq. flat time invariant

Table 5.2: Comparison of delay estimation methods for OFDM

Remarks

In OFDM systems the time synchronization has to be performed prior to the CP removing and the frequency domain conversion. Therefore, all time synchronization techniques perform in time domain. Some refinement of the delay estimators may be applied in frequency domain also.

The ML delay estimators use the structural properties of the OFDM signal. They try to identify the position of the CP in the received sequence. These methods perform well in frequency flat channels but the performance is significantly degraded frequency selective channels. This is because the CP of a particular OFDM block contains interference from the neighbor block also. The performance may be improved by using known pilot symbols on certain sub-carriers.

The correlation based methods offer an increased immunity to IBI and they usually outperform the ML methods in frequency selective channels. They require a specially designed OFDM block. The transmitted symbols on this block are drawn from a different set than the data symbols. It is not usual in practical communication systems to have different data sets. Therefore, such an approach may be just of pure theoretical interest.

Blind delay estimation may be performed also if the signal is specially designed using pulse-shaping or virtual sub-carriers. It is shown in [16] that the delay information is not preserved in the second order statistics of a pure OFDM signal.

The advantages and disadvantages of the main delay estimation methods for OFDM systems are summarized in Table 5.2

5.3 Iterative method for joint synchronization and channel estimation in OFDM transmission

In this section the contribution of the author to time delay and channel estimation problems in OFDM systems is presented. Firstly, the main assumptions under which the algorithms are designed are presented:

- A fixed wireless communication link is considered with slotted transmission typical in WLAN scenarios.
- Two equal and known training OFDM blocks are transmitted at the beginning, as in the IEEE 802.11 standard [2].
- The channels are assumed frequency-selective and time invariant over the duration of at least two OFDM blocks.
- The data signals are considered uncoded, i.i.d. and drawn from a QAM constellation.
- The additive noise is i.i.d. Gaussian distributed with zero mean and known variance.
- The data sequence, the additive noise and the channels are statistically independent.
- The carrier frequency offset is zero. The influence of the residual carrier offset on the algorithm performance is discussed also.
- The delay is deterministic and constant over the observation interval. A rough estimation of the time instance of the beginning of the transmission was performed by measuring the received signal power. The remaining delay is assumed to be smaller than the duration of the OFDM block.

The proposed method addresses the problem of parameter acquisition at the start of the transmission. The transmitted data symbols are modulated on M sub-carriers. The system model after CP addition is described by the equation (5.2). The parallel streams are converted to serial and are transmitted through a frequency selective channel with the CIR of length L_h. It is assumed that the carrier frequency offset is zero, therefore the received signal is described as in Equation (5.3) with $\epsilon = 0$.

The delayed transmitted signal may be also written as:

$$r(m) = s(m - \delta) = (1 - d)s(m - p) + ds(m - p - 1), \tag{5.14}$$

where p and d are the integer and fractional parts of the delay w.r.t. the sampling period. Equation (5.14) gives a model for the delayed signal similar to that in DS-CDMA adopted in Chapter 3 and Chapter 4. Any other model can be used since the algorithm derivation and performance does not depend on the delayed signal model. The time delay δ is assumed to be more than the CP length.

The received serial signal is passed through a serial to parallel converter and the CP is removed. The received signal vector after the CP removal is:

$$\mathbf{y}[n] = [y((n-1)M + nP + 1), \ldots, y(n(M + P))]^T . \tag{5.15}$$

It can be also written as:

$$\mathbf{y}[n] = \mathbf{R}[n]\mathbf{h} + \mathbf{w}[n], \tag{5.16}$$

where $\mathbf{w}[n]$ is the noise vector, $\mathbf{h}$ is the CIR vector of size $(L_h \times 1)$ and $\mathbf{R}[n]$ is the signal convolution matrix of size $M \times L_h$ given by:

$$\mathbf{R}[n] = \begin{bmatrix} r((n-1)M+nP+1) & r(n(M+P)) & \dots & r(n(M+P)-L_h+2) \\ r((n-1)M+nP+2) & r((n-1)M+nP+1) & \dots & r(n(M+P)-L_h+3) \\ \vdots & \vdots & \dots & \vdots \\ r(n(M+P)) & r(n(M+P)-1) & \dots & r(n(M+P)-L_h+1) \end{bmatrix} \tag{5.17}$$

The received vectors $\mathbf{y}[1]$ and $\mathbf{y}[2]$ are the result of the transmission of the same training OFDM symbol $\mathbf{r}[1]$ in a perfectly synchronized environment. If the CIR is known and taking into account the limited number of signal observations that can be used, the delay may be estimated by minimizing the following non-linear LS cost function:

$$\begin{aligned} &\mathcal{J}(\tau) = (\mathbf{y}[2] - \mathbf{R}_\tau[2]\mathbf{h})^H (\mathbf{y}[2] - \mathbf{R}_\tau[2]\mathbf{h}), \\ &\hat{\delta} = \arg \min_{\tau \in \{0,\dots,M-1\}} \mathcal{J}(\tau), \end{aligned} \tag{5.18}$$

where $\mathbf{R}_\tau[2]$ is the cyclic convolution matrix formed from the transmitted data with different delays τ. We assumed that the delay is a deterministic parameter with values in a finite set. Therefore, the minimum of the non-linear LS cost function in (5.18) can be found numerically.

In practical systems, however, the CIR is also unknown and has to be estimated. We use a LS channel estimator stemming from [56], but in the asynchronous case. An iterative scheme for joint CIR and time delay estimation can be summarized as follows:

1. Raw estimation
   - Consider an arbitrary valued vector as the initial estimate of the channel impulse response, $\hat{\mathbf{h}}_0$, and compute the first estimate of the time delay $\hat{\delta}_1$ by evaluating the cost function of (5.18) at integer values of the delay, where $\mathbf{h}$ is replaced with $\hat{\mathbf{h}}_0$. The cost function $\mathcal{J}(\tau)$ is robust to the channel estimate initialization. Simulations presented in *Paper IX* show that the LS cost function exhibits a minimum in the vicinity of the true delay even though the channel vector is randomly chosen. However, a refinement of the delay estimates is needed for a reliable data demodulation.
   - By using $\hat{\delta}_1$ refine the channel impulse response estimate, $\hat{\mathbf{h}}_1$ using a linear LS estimator:
   $$\hat{\mathbf{h}}_1 = \mathbf{R}^{\#}_{\hat{\delta}_1}[2] \frac{\mathbf{y}[1] + \mathbf{y}[2]}{2}, \tag{5.19}$$
   where $\mathbf{R}^{\#}_{\hat{\delta}_1}[2] = \left(\mathbf{R}^H_{\hat{\delta}_1}[2]\mathbf{R}_{\hat{\delta}_1}[2]\right)^{-1} \mathbf{R}^H_{\hat{\delta}_1}[2]$.
2. Refinement
   - Using $\hat{\mathbf{h}}_1$ and a finer grid search in (5.18), refine the time delay estimate, $\hat{\delta}_2$.

- Refine the channel impulse response estimate using the time delay estimate $\hat{\delta}_2$ in (5.19).

The number of iterations in the algorithm can be increased, but it is observed in the experimental results of *Paper IX* that no improvement is obtained after the second iteration.

The performance measures of the proposed algorithm adopted in the simulations are the delay estimation error and the MSE of the channel estimator. In realistic scenarios, these performance measures cannot be used since the channels and the delays are not directly observable. More appropriate in this case would be the SER or BER at the receiver output. However, the adopted performance measures are valuable quality measures of the receiver performance. The simulations conditions and results are presented and discussed in *Paper IX*.

The carrier frequency offset is assumed to be 0 during the algorithm derivation. In a realistic scenario, carrier frequency offset exists and it has to be compensated for. Otherwise a severe degradation in the receiver performance can be expected due to inter-carrier-interference. The cost function $\mathcal{J}(\tau)$ given in (5.18) is robust with regard to the frequency offset due to its quadratic form. However, the channel estimator performance may be highly degraded because of large frequency offsets. The simulation results of *Paper IX* show that for small values of the normalized frequency offset (smaller than 0.01 of the sub-carrier spacing) both estimators perform very well. For a larger frequency offsets, the channel estimator performance significantly degrades while the time delay estimator still performs well. The effect of carrier frequency offset may be mitigated by incorporating a frequency offset estimator in the algorithm. Even for large frequency offsets, the time delay is well estimated after the second iteration. Therefore, after the second iteration the algorithm proposed in [177] may be used to estimate the frequency offset. This algorithm employs the same system model setup with two identical training symbols. A third iteration is necessary in this case to refine the estimate of the channel impulse response.

5.4 Discussion

The proposed channel and delay estimation algorithm is derived assuming fixed wireless OFDM systems specific to WLAN. The parameters acquisition has to be performed fast and based on few observations. Therefore, LS estimators are adopted: a non-linear LS estimator for the delay and a linear LS estimator for the CIR. The transmission of two consecutive identical OFDM blocks [2] is exploited in order to reduce the additive noise influence. Channel estimation requires the channels to be time-invariant over two OFDM blocks while the delay estimation scheme may also be applied when the channels are time-varying. Other channel estimators can be used in conjunction with the delay estimator in such scenarios.

The proposed delay estimation algorithm does not use the CP in the estimation process. Therefore, it is robust with regard to IBI unlike the ML based methods [79, 176, 177, 195]. Another desirable property of the proposed method is that it is able to estimate fractional delays w.r.t. the sampling period. This is not the case with most of the algorithms proposed in the literature. This aspect is often neglected. If the delay is larger than the CP, a delay estimation error larger than 20% of the sampling period results in a significant loss of performance even in the noiseless case, as shown in *Paper IX*. The algorithm from [16] is also able to estimate fractional delays, but with a higher degree of computational complexity. The proposed method does not require any special design of the signal, unlike the correlation based techniques [148].

The channel estimator is a time domain method and it stems from [56], which is derived for synchronous transmission. The advantage of the time domain approaches over the frequency domain ones is a smaller estimation error since the maximum length of the CIR is significantly less than the number of sub-carriers. Frequency domain methods have to estimate the channel state information on all sub-carriers, whereas the time domain approaches only need to estimate the taps in the CIR. Given a fixed amount of data, it is easier to estimate fewer parameters. Fewer parameters leads to lower variance in the estimates.

The proposed algorithm requires the knowledge of the transmitted data on all sub-carriers for two consecutive OFDM blocks. Such an approach is in concordance with existing standards such as IEEE 802.11 [2]. Therefore, the proposed method is of real practical interest. Under conditions typical for fixed wireless communications, the proposed algorithm is able to complete two important tasks simultaneously: time synchronization and channel estimation. The estimation of the frequency offsets is not considered, but approaches using the same system model [177] may be easily accommodated into the algorithm.

Chapter 6

Summary

Wireless communication systems have received increased interest in commercial applications since the beginning of the 1980's. Following the Internet boom, wireless networks are now required to deliver high data rate multimedia services in addition to low data rate speech and text messaging services. Consequently, advanced signal processing techniques are needed at the physical layer level in order to ensure the desired signal integrity. Receiver algorithms able to cope with the impairment specific to wireless networks are of interest. Time-varying multipath fading channels are always encountered in such systems, the power control is imperfect and the active users need to be synchronized prior to data demodulation. One efficient strategy for increasing wireless communication link reliability is to use diversity techniques, in the form of time, frequency or space diversity [196]. The radio spectrum is a scarce resource. Hence, receiver algorithms that use very little training data for the estimation of the parameters are of great interest. Consequently, blind methods may appear to present an appealing solution. However, identifiability problems as well as slow convergence limit their applicability to low mobility scenarios. Using small amounts of training data along side blind methods leads to more efficient and robust semi-blind algorithms.

The feasibility of blind equalization for GSM-EDGE networks is studied in this thesis. It is shown that linearized GMSK signal is feasible for blind equalization. The signal itself does not induce identifiability problems for the SOCS-based blind equalizers. Only the transmission channel may introduce such problems. This risk may be reduced by using array antennas at the receiver instead of oversampling a single antenna. Simulations performed for GSM and EDGE scenarios show that FS-SOCS blind equalizers achieve a better performance than HOS based blind equalizers.

A novel receiver structure for uplink long-code DS-CDMA is developed in this thesis. Multiple antennas are assumed at the receiver in order to take advantage of the improved SNR and the spatial diversity. The system model is characterized by a channel matrix which also contains information about the users' propagation delays. An adaptive multichannel estimator is derived, which is also capable of tracking the time-variations of the channels. The SER performance of the algorithm is studied using an optimal MMSE multiuser equalizer that is found based on the estimated channel matrix. The values of the channel estimator learning parameters are found which guarantee algorithm convergence. Low complexity synchronization algorithms are also proposed based on the special structure of the channel matrix. In particular, a synchronization method suitable for adaptive channel estimation delivers a high probability of delay acquisition even in very low SNR scenarios. The large sample behavior of this method is studied. The proposed receiver structure is derived for long-code CDMA unlike most of the algorithms presented in the literature. Therefore, it is a solution which is of practical interest, since all commercial DS-CDMA based wireless communication systems use long-codes. The experimental results obtained in realistic scenarios show that the algorithm achieves good overall performance in the face of high background noise and near-far effects.

An iterative method for time synchronization and channel estimation for OFDM systems is derived in this thesis. Assuming a scenario specific to fixed wireless networks, the channels and delays are estimated in time domain using a two step procedure: raw estimation and refinement of the estimates. Both steps are performed on the same received data. The proposed algorithm may be extended to the estimation of the frequency offset even though it is not considered here. Synchronization errors of a fraction of the sampling period result in significant performance loss in the receiver. The proposed algorithm estimates fractional delays unlike most of the methods in the literature. The simulation results show that high quality channel and delay estimates are obtained in scenarios with frequency selective channels and SNR specific to fixed wireless OFDM links.

Possible topics of future research work are the synchronization in satellite position location systems and channel estimation and synchronization for hybrid multicarrier CDMA (MC-CDMA) systems. The algorithms derived in this thesis may be further extended and adapted to such applications. High precision positioning systems (GPS and Galileo) are DS-CDMA based systems which use very long spreading sequences with a high chip frequency. These systems have special characteristics such as extremely low signal power and high power intentional and non-intentional interference. In such difficult conditions, the delay estimation has to be very accurate, especially for applications such as aircraft landing and take-off. Very efficient signal processing techniques have to be employed for the delay estimation in such systems. The MC-CDMA brings together the advantages of both CDMA and OFDM in order to provide high data rate wireless links. This system is more complicated than CDMA or OFDM and therefore requires more demanding signal processing techniques at the physical layer. MC-CDMA is very sensitive to time and frequency synchronization errors as well as MUI and these issues have to be carefully considered.

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