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SOFT DETECTION AND DECODING IN WIDEBAND CDMA SYSTEMS

Kimmo Kettunen

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ABSTRACT

A major shift is taking place in the world of telecommunications towards a communications environment where a range of new data services will be available for mobile users. This shift is already visible in several areas of wireless communications, including cellular systems, wireless LANs, and satellite systems. The provision of flexible high-quality wireless data services requires a new approach on both the radio interface specification and the design and the implementation of the various transceiver algorithms. On the other hand, when the processing power available in the receivers increases, more complex receiver algorithms become feasible.

The general problem addressed in this thesis is the application of soft detection and decoding algorithms in the wideband code division multiple access (WCDMA) receivers, both in the base stations and in the mobile terminals, so that good performance is achieved but that the computational complexity remains acceptable. In particular, two applications of soft detection and soft decoding are studied: coded multiuser detection in the CDMA base station and improved RAKE-based reception employing soft detection in the mobile terminal.

For coded multiuser detection, we propose a novel receiver structure that utilizes the decoding information for multiuser detection. We analyze the performance and derive lower bounds for the capacity of interference cancellation CDMA receivers when using channel coding to improve the reliability of tentative decisions.

For soft decision and decoding techniques in the CDMA downlink, we propose a modified maximal ratio combining (MRC) scheme that is more suitable for RAKE receivers in WCDMA mobile terminals than the conventional MRC scheme. We also introduce an improved soft-output RAKE detector that is especially suitable for low spreading gains and high-order modulation schemes. Finally we analyze the gain obtained through the use of Brennan's MRC scheme and our modified MRC scheme.

Throughout this thesis Bayesian networks are utilized to develop algorithms for soft detection and decoding problems. This approach originates from the initial stages of this research, where Bayesian networks and algorithms using such graphical models (e.g. the so-called sum-product algorithm) were used to identify new receiver algorithms. In the end, this viewpoint may not be

easily noticeable in the final form of the algorithms, mainly because the practical efficiency considerations forced us to select simplified variants of the algorithms. However, this viewpoint is important to emphasize the underlying connection between the apparently different soft detection and decision algorithms described in this thesis.

Keywords — CDMA, soft detection, soft decoding, coded multiuser detection, RAKE receiver, sum-product algorithm, iterative methods

PREFACE

The work constituting this thesis was carried out in the Signal Processing Laboratory and the Networking Laboratory (formerly Laboratory of Telecommunications Technology) at Helsinki University of Technology. I wish to express my deep gratitude to my supervisor Prof. Timo Laakso for his interest and advice as well as for allowing a significant amount of academic freedom in my research. I would also like to thank Prof. Iiro Hartimo for the opportunity to work at the Signal Processing Laboratory as well as the laboratory secretaries Anne Jääskeläinen and Mirja Lemetyinen for the help with all the practical issues and arrangements.

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LIST OF PUBLICATIONS

[P1] K. Kettunen, T. Laakso, "Iterative multiuser receiver utilizing soft decoding information," in Proceedings *IEEE International Communications Conference*, ICC'99, Vancouver, BC, Canada, pp. 942-946, June 1999.

[P2] K. Kettunen, "Iterative multiuser receiver/decoders with enhanced variance estimation," in Proceedings *IEEE 49th Vehicular Technology Conference*, VTC'99, Houston, Texas, USA, pp. 2318-2322, May 1999.

[P3] K. Kettunen, "Performance of coded multistage detection in correlated Rayleigh channels", in Proceedings *X European Signal Processing Conference*, EUSIPCO-2000, Tampere, Finland, pp. 565-568, September 2000.

[P4] K. Kettunen, "Enhanced maximal ratio combining scheme for RAKE receivers in WCDMA mobile terminals", *IEE Electronics Letters* vol. 37, no. 8 pp. 522-524, 12th April 2001.

[P5] K. Kettunen, J. Lilleberg, "Decoding metric of downlink CDMA RAKE receivers using bit-interleaved coded modulation", accepted to *Wireless Personal Communications*, May 2002.

[P6] K. Kettunen, "Enhanced maximal ratio combining for RAKE receivers in mobile CDMA terminals", in Proceedings *5th Nordic Signal Processing Symposium*, NORSIG 2002, on board Hurtigruten, Norway, pp. 217-221, October 2002.

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LIST OF ACRONYMS

3GPP	The 3rd Generation Partnership Project
APP	A Posteriori Probability
AWGN	Additive White Gaussian Noise
BCJR	Bahl, Cocke, Jelinek and Raviv
BER	Bit Error Rate
BPSK	Binary Phase Shift Keying
DFMD	Decision-Feedback Multiuser Detector
DS-CDMA	Direct Sequence CDMA
CDMA	Code Division Multiple Access
EDGE	Enhanced Data rates for GSM Evolution
ETSI	European Telecommunications Standards Institute
FDD	Frequency Division Duplex
FDMA	Frequency Division Multiple Access
FM	Frequency Modulation
GPRS	General Packet Radio Service
GSM	Global System for Mobile communications
HSCSD	High-speed Circuit Switched Data
HSDPA	High-Speed Downlink Packet Access
IC	Interference Cancellation
IMT-2000	International Mobile Telecommunications 2000
ISI	Intersymbol Inference

ITU	International Telecommunication Union
MAI	Multiple Access Interference
MAP	Maximum A Posteriori
MF	Matched Filter
ML	Maximum Likelihood
MLSE	Maximum Likelihood Sequence Estimator
MMSE	Minimum-Mean-Squared-Error
MMSE DF	Minimum-Mean-Squared-Error Decision-Feedback
MRC	Maximum Ratio Combining
MUD	Multiuser Detection
NMT	Nordic Mobile Telephone system
OSOME	Optimum Soft-Output Multiuser Estimation
PC	Power Control
PDF	Probability Density Function
QAM	Quadrature Amplitude Modulation
RCRD	Reduced-Complexity Recursive Detector
RS	Reed-Solomon
SISO	Soft-Input-Soft-Output
SSOME	Suboptimum Soft-Output Multiuser Estimation
TCM	Trellis Coded Modulation
TDMA	Time Division Multiple Access
UMTS	Universal Mobile Telecommunications System
UTRAN	UMTS Terrestrial Radio Access Network
WCDMA	Wideband CDMA

LIST OF SYMBOLS AND NOTATIONS

H_0	Null hypothesis
H_1	Alternative hypothesis
H_k	Hypothesis in multiple hypothesis case
$y(t)$	Received signal
$s(t)$	Signal of interest
$s_k(t)$	Signal of interest in multiple hypothesis case
$n(t)$	White Gaussian noise
$L(T)$	Likelihood ratio
M	Number of hypotheses
M	Number of modulation symbols
$(\cdot)^{\mathrm{T}}$	Transpose of a real-valued vector
$\mathbf{u}$	Information bit vector
$\mathbf{y}$	Received signal sample vector
$\mathbf{n}$	Vector of additive white Gaussian noise samples
$\mathbf{s}$	Vector of states
$\mathbf{x}$	Vector of output bits from a convolutional encoder
$p(\mathbf{u}\|\mathbf{y})$	Probability distribution of $\mathbf{u}$ conditioned on $\mathbf{y}$
$p(\mathbf{u},\mathbf{y})$	Joint probability distribution of $\mathbf{u}$ and $\mathbf{y}$
x_k	The k^{th} element of arbitrary vector $\mathbf{x}$
$f(s_i)$	Output bit generation rule for a convolutional encoder

$g(s_{i-1}, u_i)$	State transition rule for a convolutional encoder
$a \oplus b$	Modulo 2 addition
$\hat{\mathbf{u}}$	Vector of detected information bits
$\max\limits_{\mathbf{u}\in U} v(\mathbf{u})$	Vector **u** that produces the maximum value for some function $v(\mathbf{u})$
$\Phi(\mathbf{u})$	The output of the encoder with input **u**
$\mathbf{H}$	Channel matrix
σ^2	Variance
$\mathbf{R}$	Cross correlation matrix
$\mathbf{A}$	Amplitude matrix
K	Number of users
$\mathrm{sgn}(\cdot)$	A vector containing the signs of the argument vector elements
$E(\cdot)$	Expectation value
$\mathbf{I}$	Identity matrix
Q	Code rate
R	Inverse of the code rate $1/Q$
W	Constraint length of the convolutional code
$y_i^{(l)}$	The lth RAKE finger output sample in mobile terminal receiver
$\rho(i,l,p,j,k)$	Correlation coefficient between different symbols and users in different paths
$h_j^{(p)}$	Channel coefficients for pth path at time j
x_{ik}	Coded information symbol for user k at time i
s_{ik}	Channel encoder state for user k at time i
$\mathbf{y}_{\mathrm{i}}$	Vector of matched filter output samples for all users at time i
$\mathbf{x}_{\mathrm{i}}$	Vector of transmitted data symbols for all users at time i

$\mathbf{n}_i$	Vector of white Gaussian noise samples for all users at time *i*
$u_j^{(k)}$	Information symbols for user *k* at time *j*
$y_i^{(k)}$	Matched filter output sample for user *k* at time *i*
$x_i^{(k)}$	Transmitted data symbol for user *k* at time *i*
$s_j^{(k)}$	State of the channel encoder for user *k* at time *j*
λ	Likelihood message used in the sum-product algorithm
$\lambda(Y \to X)(x)$	Likelihood message from node representing random variable *Y* to node representing random variable *X*
π	Probability message used in the sum-product algorithm
$\pi(X \to Y)(x)$	Probability message from node representing random variable *X* to node representing random variable *Y*
$p(u_j^{(k)} = u)$	Probability that $u_j^{(k)}$ is equal to *u*
$\sum_{s',u:g(s',u)=s}$	Sum over all possible value pairs (*s'*,*u*) that satisfy g(*s'*,*u*)=*s*
$\sum_{s:f_l(s)=x_{R(j+1)+l}^{(k)}}$	Sum over all possible values of *s* satisfying $f_l(s) = x_{R(j+1)+l}^{(k)}$
$\sum_{\mathbf{x}_i:x_i^{(k)}=x}$	Sum over all possible vectors $\mathbf{x}_i$ such that the k^{th} element of the vector is *x*
$\prod_{h \neq k}$	Product over all possible values of *h* except *k*
$\max_{\mathbf{x}_i:x_i^{(k)}=x}$	Maximum over all possible vectors $\mathbf{x}_i$ such that the k^{th} element of the vector is *x*
$\sum_{h \neq k}$	Sum over all possible values of *h* except *k*

$\left(\mathbf{RA}\hat{\mathbf{x}}_i\right)^{(k)}$	The k^{th} element of the vector $\mathbf{RA}\hat{\mathbf{x}}_i$
$y_l(n)$	The lth RAKE finger output sample in mobile terminal receiver at time n
$h_l(n)$	The lth path channel coefficient at time n
$x(n)$	Coded channel symbol for the desired user at time n
$w_l(n)$	Combined channel noise and interference sample at time n
σ_l^2	Variance of $w_l(n)$
$\hat{h}_l(n)$	Channel estimate for the lth path channel coefficient at time n
$\sigma_{z_l}^2$	Average mean-squared error of $\hat{h}_l(n)$
F	Arbitrary positive real constant
$\mathrm{Re}(\cdot)$	Real part of a complex number

1 INTRODUCTION

A major shift is taking place in the world of telecommunications towards an era of "tetherless" communications where a range of new data services is available for mobile users. This shift is already visible in several areas of wireless communications, including cellular systems, wireless LANs, and satellite systems.

In the area of cellular mobile systems, the existing 2nd-generation systems are rapidly being upgraded for the provision of these new data services. For instance in GSM, the standardization of the high-speed circuit switched data services (HSCSD) as well as packet switched data services (GPRS) has already been completed. A major step in the introduction of the new data services has been the 3rd generation cellular systems such as Universal Mobile Telecommunications System (UMTS) specified by 3GPP and a part of the IMT-2000 family under development in ITU. There is also an ongoing activity for the evolution of UMTS Terrestrial Radio Access Network (UTRAN) beyond the original requirements, the high-speed downlink packet access (HSDPA), which is aiming at high peak data rates and low overall delays [PDF01].

The provision of this kind of high-speed, high-quality wireless data services requires a new approach on both the radio interface specification and on the design and the implementation of the various transceiver algorithms. There is a need for further development of existing algorithms as well as for the creation of completely new solutions. Recognizing this need, the broad framework of this research is the development of advanced receiver algorithms to be used in base station and mobile terminal receivers for UTRAN Frequency Division Duplex (FDD) mode, where the Wideband Code Division Multiple Access (WCDMA) technology is used.

Looking at possible new directions, the success of iterative decoding for Turbo codes [HeW99] suggests that a new way to devise these high-performance algorithms could be found by considering a probabilistic approach where soft information presenting the probabilities of different alternatives is used in detection and decoding processes. Many detection, decoding and estimation problems can be reduced to the estimation of certain probabilities. Detection and decoding algorithms that actually produce these probabilities or some continuous-value metrics based on these are called in this thesis soft detection and decoding methods (See Chapter 3 for details). There are known algorithms that may be used for the estimation of the probabilities such as the *sum-product algorithm* (also called the *generalized forward-backward algorithm*). Many of these algorithms use some graphical description of the dependencies between the random variables in the system, such as Bayesian networks [Fre98]. However, these algorithms may have a high computational complexity. Thus the main problem remains how to derive soft detection and decoding algorithms for CDMA receivers with good performance while keeping the computational complexity acceptable.

This thesis considers the above problem and studies the application of soft detection and decoding methods in two specific cases: coded multiuser detection in the CDMA base station, and improved RAKE-based reception employing soft detection in the mobile terminal. The initial approach in this research was to describe these soft detection and decoding problems using Bayesian networks and then to apply some variant of the sum-product algorithm. However, since there is a need to have algorithms with reduced complexity (especially for the mobile terminal), the final algorithms are quite specialized variants of the sum-product algorithm that may be hard to recognize. To emphasize this initial theme in this research, Bayesian networks are used whenever possible to illustrate the addressed soft detection and decoding problems.

The thesis structure is as follows: in Chapter 2, a short background on wireless systems and receivers is given; in Chapter 3, soft detection and decoding is introduced starting from detection theory and introducing soft detection by considering reduced complexity methods and in particular iterative methods, where the soft detection and decoding play a key role. The chapter is concluded by a review of soft detection and decoding in wideband CDMA systems.

Chapter 4 studies the application of soft detection for coded multiuser detection in CDMA base stations. The state-of-the-art research on coded multiuser receivers is reviewed and the emphasis is on iterative joint multiuser receivers, the type of receivers considered in publications [P1] and [P2]. Finally, some system issues of iterative joint multiuser receivers are considered that are related the analysis presented in [P3].

In Chapter 5, the application of soft detection for an improved RAKE-based reception in the mobile terminal is studied. The approach used to derive the improved RAKE receivers proposed in [P4], [P5] and [P6] is presented. In Chapter 6, a summary of the publications is presented and in Chapter 7 some concluding remarks are made. Possibilities for future work are discussed in Chapter 8.

2 BACKGROUND

The history of wireless communication began in the late 19th century when Hertz, Marconi, Tesla, and many other scientists and engineers experimented with the transmission and reception of electromagnetic waves, predicted by Maxwell's theory published in 1864 [Max64]. In 1888, Hertz experimentally verified the existence of electromagnetic waves [CiW95]. The practical significance of this discovery became gradually apparent and in 1896 Marconi applied for a patent utilizing the electromagnetic waves for wireless communications [Nig97]. Followed by Tesla's demonstration of a radio remotely controlled boat in 1898 [MaB01], the first wireless ship-to-shore telegraph link by Marconi the same year [EAS95] and the first trans-atlantic wireless transmission in 1901 [Nig97], these events may be considered as the start of wireless communications.

From the beginning of the 20th century, the progress in radio technology was rapid. But even though many key concepts such as the cellular model, spread spectrum techniques and digital modulation were known more than 50 years ago, mobile telephone services did not appear in useful forms until the early 1960s, and even then only as elaborate adaptations of simple dispatching systems [RWO95]. The convenience of these early mobile systems was severely limited, and their maximum capacity was tiny by today's standards. The situation changed in the early 1980's, when the first *cellular* mobile systems went into service in Japan and in the United States. These were analog full duplex FM systems, but still they became quickly popular, as did other similar systems, such as NMT. The next major step was the introduction of the 2nd generation digital cellular systems, like the GSM. Today, the popularity of 2nd generation systems has exceeded all expectations and with the emerging new data services and the introduction of 3rd generation systems, the future of wireless communications has great potential.

In the rest of the chapter we give a brief overview of the cellular radio and the fundamentals of digital communications, the two concepts that have played a key role in the development of mobile communications. Finally we will present a reference receiver model that is used in this thesis to derive the soft detection and decoding methods.

2.1 CELLULAR SYSTEMS

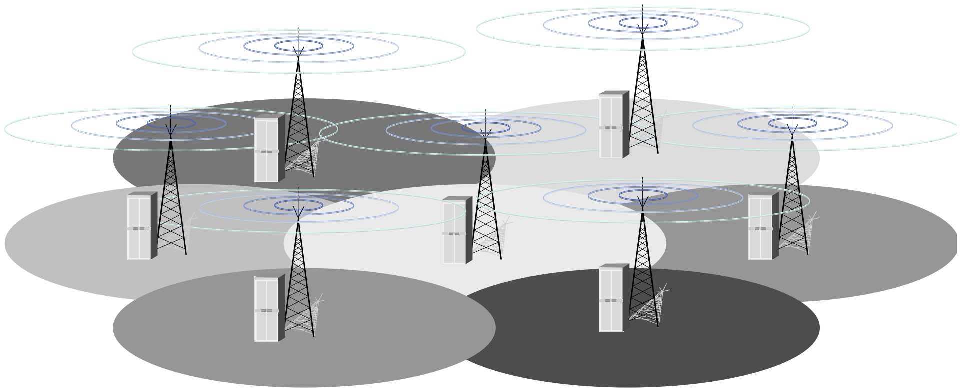

Figure 1 Cellular network structure

In early mobile radio systems, a small set of frequencies was used for a huge geographical area. The transmitters were so powerful that their operating frequencies could not be reused for hundreds of kilometers. This was a major limitation to the capacity of the system; once a channel was in use, the channel was not reuseable over the whole coverage area, even though the need for a mobile communication channel was confined to a small part of the network's service area. This prohibited the mass deployment of mobile communications.

A new approach was proposed, where the total frequency band was split to several sub-bands. These sub-bands were allocated to different geographical cells with a procedure where neighborhood cells were allocated different sub-bands e.g. according to Figure 1. In this way several cells could coexist spatially and so the cellular structure was born.

In practice special care needs to be taken in order to limit the interference between cells. This may be achieved by a suitable frequency allocation scheme or by utilizing spread spectrum techniques. In addition, the frequency range used should be high enough to limit the signal propagation. With suitable equipment, roaming and hand-overs can be used to be both reachable and have uninterrupted connection established while moving from one cell to another.

2.2 FUNDAMENTALS OF DIGITAL COMMUNICATIONS

2.2.1 Elements of a Digital Communications system

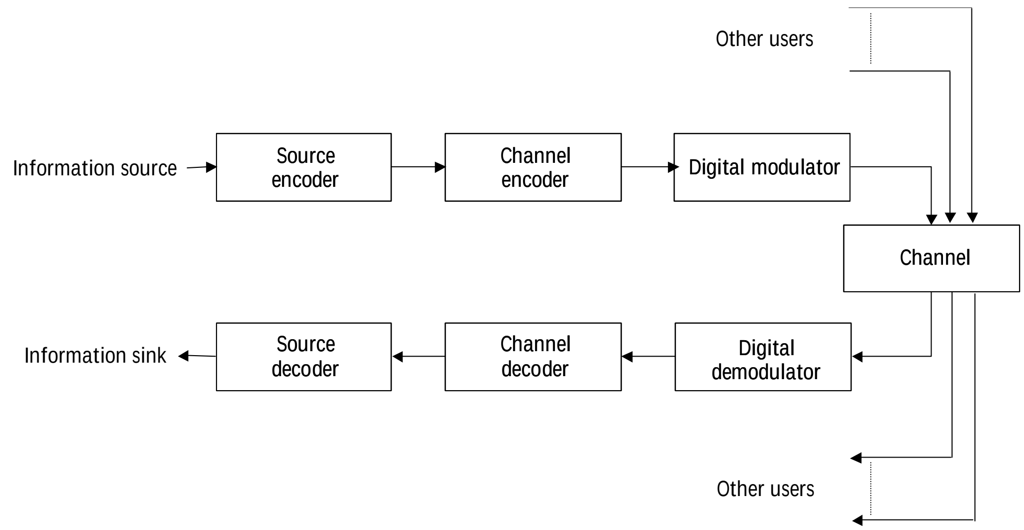

Figure 2 Basic elements of a digital communications system (Adapted from [Pro95])

In a cellular system both uplink (terminal-to-base station) and downlink (base station-to-terminal) communication is required between the mobile terminals and the base station. With digital cellular systems, the communication system for both uplink and downlink are usually arranged using the generic digital communication system structure shown in Figure 2. The task of the communication system is to relay the information between the information source and the sink. For the uplink, the information source is in the mobile terminal, it can for instance be an A/D converter that converts the speech signal to digital information. For the downlink, the information source is somewhere in the cellular network or in another mobile terminal.

The aim of the source encoder is to remove the redundancy that is present in every natural information source. The output of the *source encoder* is passed to the *channel encoder*. The purpose of the channel encoder is to introduce, in a very particular manner, some redundancy in the input sequence, which can be used for error detection and correction in the receiver. The output of the channel encoder is passed to the *digital modulator*, which serves as an interface to the communications channel. In the case of cellular communication, several users typically share the channel and some multiple access technique needs to be employed. The different multiple access methods are discussed further in Section 2.2.2.

In the receiver, each transmitter block has a counterpart that complements the function of the transmitter block in question. The *digital demodulator* processes the waveform received through the channel and reduces the waveforms to a sequence of numbers that present the estimates of the transmitted data symbols. In this process which is often referred to as *detection*, the used multiple access technique is also taken into account. This sequence of numbers is passed to the channel decoder, which attempts to reconstruct the original input of the *channel encoder* using the information of the redundancy structure, that is, the channel coding information. Finally the output of the channel decoder is fed to the *source decoder*, which tries to reconstruct the original message.

The generic digital communications system structure shown in Figure 2 does not describe all the details in the system. Thus, depending on the focus, a more detailed description of some parts of the system may be needed. In this thesis, the main focus is on the methods used in the wideband CDMA receivers for detection and channel decoding. The above receiver structure needs to be elaborated for those parts. This is done in Section 2.3 where we describe a more detailed reference receiver structure.

2.2.2 Multiple Access Techniques

In cellular communications, the total capacity within a cell needs to be divided between the existing users. In addition to the duplexing, some multiple access method is required to support the simultaneous access to the radio channel by all users. Usually, the basic approach is to employ signals that are orthogonal or at least nearly orthogonal. Then, correlators that project the received signal into the subspace of the desired signal can be employed to extract it, ideally without interference from other transmissions. The orthogonal signal set can be selected in a variety of ways. The most commonly used multiple access techniques result when the orthogonal signal sets are obtained by selecting signals that are separated either in frequency domain, time domain or code domain.

In the frequency domain signals, which occupy non-overlapping frequency bands, can be separated using appropriate bandpass filters. Hence, signals can be transmitted simultaneously without significantly interfering with each other. This method of providing multiple access capabilities is called frequency-division multiple access (FDMA).

In the time domain, signals are transmitted in non-overlapping time slots for instance in a round-robin fashion. The signals occupy the same frequency band but can be separated based on their time of arrival. This method of providing multiple access capabilities is called time-division multiple access (TDMA).

In the code domain, the signals are transmitted simultaneously and even occupy the same frequency band. However, the signals are selected to be nearly mutually orthogonal. Thus, correlators can extract individual signals from the mixture of signals, although some amount of multiple access interference (MAI) will usually be present due to the non-orthogonality. This method of providing multiple access capabilities is called code-division multiple access (CDMA).

2.3 REFERENCE CDMA RECEIVER STRUCTURE

The basic model for digital communications shown in Figure 2 is presents a high level view of the system. In each block there is a hidden structure that needs to be taken into account in more specific discussions. This thesis considers soft detection and decoding methods, where a feedback from the channel decoder to the detector often plays a key role. These methods are also closely related to iterative decoding methods that utilize a particular channel decoder structure with constituent decoders and a feedback loop [HeW99]. In order to have a unified framework for the purposes of this thesis, we present a reference CDMA receiver structure that is used in the subsequent discussions.The reference structure of a CDMA receiver is shown in Figure 3. The detector can be for instance some variant of the coded matched filter detector, RAKE based detector, multiuser detector or a combination of those. The output of the detector is passed (reference point A in the figure) to the channel decoder. The channel decoder may consist of one or several constituent decoders. One decoder is used e.g. when convolutional coding is used for speech and several constituent decoders are used for concatenated and Turbo codes. The information is passed from the “inner” decoder to the “outer” one (reference point B) and in the case of iterative decoding there is also a feedback loop (reference point C). There may also be some feedback between channel coding output and the detection (reference point D) e.g. for iterative joint multiuser detection and decoding. Finally the output of the channel decoder is passed (Reference point E) to the source decoder, which produces the final output information.

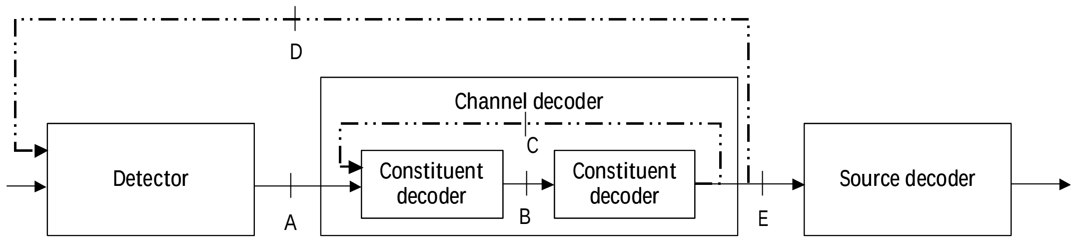

Figure 3 Reference CDMA Receiver Structure

The information passed at the reference points may only contain estimates of the bits or symbols. Alternatively, it may also contain some measure indicating how reliable the estimate is. In the former case we say that *hard information* is passed while in the latter case we say that *soft information* is passed. In principle, either hard or soft information can be passed at all the reference points in Figure 3, although for reference point C, only soft information passing has proven beneficial in practice [HeW99].

We use the term *soft detection* for the case where soft information is passed at reference point A. Alternatively, when only hard information is passed at reference point A, term *hard detection* is used. When soft information is produced in the output of either the channel decoder or a constituent decoder (reference points B, C, D and/or E, depending on the case), a term *soft decoding* is used. Since the soft decoding in practice requires also soft input in the decoder, the term *soft-input-soft-output (SISO) decoder* [BeM96] is often used for decoders performing soft detection.

Hard decoding has two variants. When a channel (or constituent) decoder has soft input (in reference point A or B), but produces hard information in the output, a term *soft decision decoder* is used. When even the input is hard information, a term *hard decision decoder* is used. It is clear from these definitions that for a soft decision channel decoder, soft detection must be used in the detector.

The CDMA receivers studied in this thesis are an iterative joint multiuser receiver for the base stations and an improved RAKE receiver for mobile terminals. The iterative joint multiuser receiver considered in this thesis uses soft detection and a SISO decoder for a convolutional code. Thus there is only one constituent decoder and soft information is passed at reference point A. Receiver variants both with soft information and hard information feedback from the decoding at reference point D are considered.

In the improved RAKE receiver for mobile terminals the feedback at reference point D is not used in order to reduce the receiver complexity, which is especially important in the mobile terminal receiver. Thus a soft output RAKE receiver is used followed by soft decision decoding. Thus only one constituent decoder is used and soft information is only passed at reference point A.

3 SOFT DETECTION AND DECODING

In Section 2.3 soft detection and soft decoding were briefly introduced. In this chapter we give an overview of detection theory and discuss soft detection and soft decoding more thoroughly in the context of detection theory, where soft detection and soft decoding play a central role especially in reduced complexity detection methods, which are often applicable in cases, such as channel decoding, where there are so many decision alternatives that the straightforward extension of the classical binary detection is not practical. These methods typically utilize some underlying structure of the problem. We use dependency graphs (Bayesian networks to be precise) to describe the structure and show how different structures are utilized in various algorithms. Finally, we discuss the detection problems arising in wideband CDMA systems and show how these problems can be solved with different algorithms when certain simplifications are made.

3.1 DETECTION OF RANDOM PROCESSES

The goal of signal detection (and estimation) is to process information-bearing signal in order to draw some conclusions about the information that they contain. This can be modeled as extracting information about a random process by using the output of another, dependent random process. As such it is closely related to the problem of statistical inference and shares the common foundation laid by the classical work of Bayes [Bayes], Gauss [Gauss], Fisher [Fis22], and Neyman and Pearson [NeP33]. A good review of detection theory is given by Kailath and Poor in [KaP98].

In most signal detection methods the decisions are based on probabilistic inference. This means that a set of (conditional) probabilities or some metric derived from those is calculated and the decision is made based on these. For instance, when making the detection decision, the alternative that corresponds to the maximum *a posteriori* probability, may be selected or, in binary cases, the sign of the log likelihood ratio gives the selected alternative ([Poo94]). According to our definition, *soft detection and decoding methods* are algorithms that produce the probabilities or other continuous-value metrics that are used in some detection algorithm. The difference between soft detection and soft decoding in this context is that soft detection is used for cases where there are only a few alternatives (e.g. binary or M-ary signals), whereas soft decoding is used for soft detection of sequences that are generated by some kind of channel encoder.

On the other hand, *hard detection and decoding* methods produce one specific selection of the alternative decision possibilities without any information of the reliability of the decision. These methods may be used as a part of a larger detection algorithm. These terms should not be confused with soft and hard decision decoding defined in Section 2.3. Recall that soft and hard decision decoding are both hard decoding methods, but in soft decision decoding the input is soft information, that is a set of probability distributions or some derived metric, like log-likelihood ratio. In fact, hard decision coding is an example where a hard detection method (hard detection of signals corresponding to individual code word symbols) is a part of a larger detection algorithm (code sequence detection).

3.2 CLASSICAL DETECTION THEORY

The basic classical detection problem is the detection of signals in white Gaussian noise ([Nor43]). There one needs to choose between two hypotheses of the form

$$H_0 : y(t) = n(t), \quad 0 \le t \le T \tag{1}$$

and

$$H_1 : y(t) = s(t) + n(t), \quad 0 \le t \le T \tag{2}$$

where $s(t)$ represents the signal of interest and $n(t)$ is white Gaussian noise. The signal may be completely known, known except for a few random or unknown parameters (e.g. $s(t) = \alpha A(t)\cos(\omega_0 t + \theta)$), or a random process.

The case of a known signal is covered in basic textbooks. As usual, the problem can be reduced to the calculation of the likelihood ratio, which in this case can be written as [WoJ65]:

$$L(T) = \exp\left\{ \int_0^T s(t)y(t)\,dt - \frac{1}{2}\int_0^T y^2(t)\,dt \right\}. \tag{3}$$

From this formulation it is evident that the solution is equivalent to a detector using matched filter receiver, which is optimal in the signal-to-noise ratio sense and originates from the early work on RADAR detection [Nor43]. The case of a known signal with unknown or random parameters has also been studied in several specific cases; see e.g. [Poo94].

This basic problem can be extended to a case where the signal is a random process, for instance a Gaussian random process. Another way of extending the problem is by allowing the noise to be colored or even non-Gaussian. See [KaP98] for a review on these cases.

One can generalize the binary case to the case of multiple hypothesis of the form

$$H_k : y(t) = s_k(t) + n(t), \quad k = 1, 2, \ldots, M \tag{4}$$

The multiple hypothesis case can be handled in most cases by introducing a dummy hypothesis, $H_0 : y(t) = n(t)$, and then using the chain rule for likelihood ratios [Poo94]. Typically, the complexity of the solution grows linearly with *M*.

3.3 REDUCED COMPLEXITY METHODS

Classical detection theory gives sufficient tools for binary detection as well as for multiple-hypothesis case, when the number of alternative hypotheses is limited. In digital communications, the cases of multiple hypotheses arise in two basic situations: detection of *M*-ary signaling alphabet and the joint detection of statistically dependent multiple data transmissions. In the *M*-ary signaling case, the number of hypotheses *M* is often small (e.g. 8 or 16) and the complexity is manageable. The second case arises in applications such as coded communications and multiple-access communications. In these applications the entire sequence or group of symbols must be detected jointly for optimal detection. If the number of *M*-ary symbols to be jointly detected is *N*, then the number of possible hypotheses is M^N. This number is so large in many practical detection applications that the linear complexity of the methods reviewed in the previous section is not feasible. Thus some form of complexity reduction is necessary. Fortunately many practical applications can be described (with sufficient accuracy) with models that have suitable structure so that the complexity of optimal detection can be substantially reduced. In this section we describe how complexity can be reduced in hard sequence detection where the sequence likelihoods (*a priori* probabilities) are used and in iterative sequence detection, where the symbol-by-symbol MAP (maximum *a posteriori* probability) criterion is used.

One approach to complexity reduction is to consider the stochastic structure of the system. In this viewpoint, the structure describes the dependencies between different random variables in the system model. Often many problems have stochastic structure that simplifies the calculation of various probability distributions of interest. This naturally reduces the complexity of soft detection.

For hard sequence detection these simplifications typically also allow the application of dynamic programming substantially reducing the complexity [KaP98]. This approach can be used to obtain many well-known detection algorithms such as the *Viterbi algorithm* for detecting convolutionally encoded data transmitted over memoryless channels [Omu69], [Vit67], the *maximum likelihood sequence estimator* (MLSE) for equalizing linearly dispersive channels [For72] and *multiuser detectors* (MUD) for demodulating non-orthogonally multiplexed data [Ver86], [Ver98]. This approach is discussed in Section 3.3.1.

With symbol-by-symbol *a posteriori* probability calculations, a different approach is preferable. For calculation of probability distributions, the dependencies between different random variables can be presented with a suitable graphical model such as Bayesian network [Pea88], factor graph [FKL97] or some other variant. A good overview on different graphical models from the digital communications point of view is given in [Fre98]. In brief, the various graphical models can be used to develop algorithms for inferring the distributions of selected random variables in the system model given the observed values of some other random variables. Examples of these algorithms include the *forward-backward algorithm* [BaP66] for chain type structures and *sum-product algorithm* [KFL01] for singly-connected graphical models. A good review of these and various other related algorithms can be found in [AjM00] and [KFL01]. These algorithms are essentially generalized forms of soft detection and soft decoding algorithms, which calculate probability distributions for certain random variables (presenting often the transmitted information) in a model describing the communications system. The use of these methods for iterative sequence detection is discussed in Section 3.3.2.

Here, to give a more specific example we consider a simple case where a information bit vector $\mathbf{u} = (u_0, u_1, u_2)^{\mathrm{T}}$ is transmitted using BPSK modulation in an AWGN channel. The received vector is thus

$$\mathbf{y} = (y_0, y_1, y_2)^{\mathrm{T}} = \mathbf{u} + \mathbf{n}\,, \tag{5}$$

where $\mathbf{n} = (n_0, n_1, n_2)^{\mathrm{T}}$ is a vector of additive white Gaussian noise samples. Figure 4 shows the Bayesian network for the system that describes the dependencies between the variables. Note that the information bits are assumed independent. The random variables presenting noise are shown as dashed, because conventionally these are not shown and instead the distribution of y_k is modified to include the effect of noise. Here we include also those for clarity. For simplicity of the notations we consider a receiver where the detection is done by finding the information bit

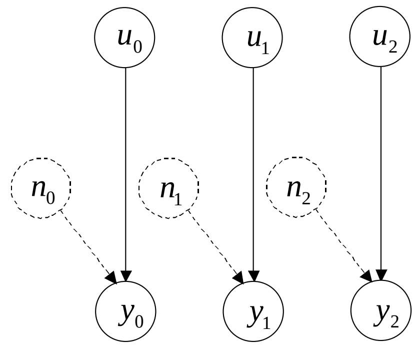

Figure 4 A simple Bayesian network for BPSK modulation in AWGN channel

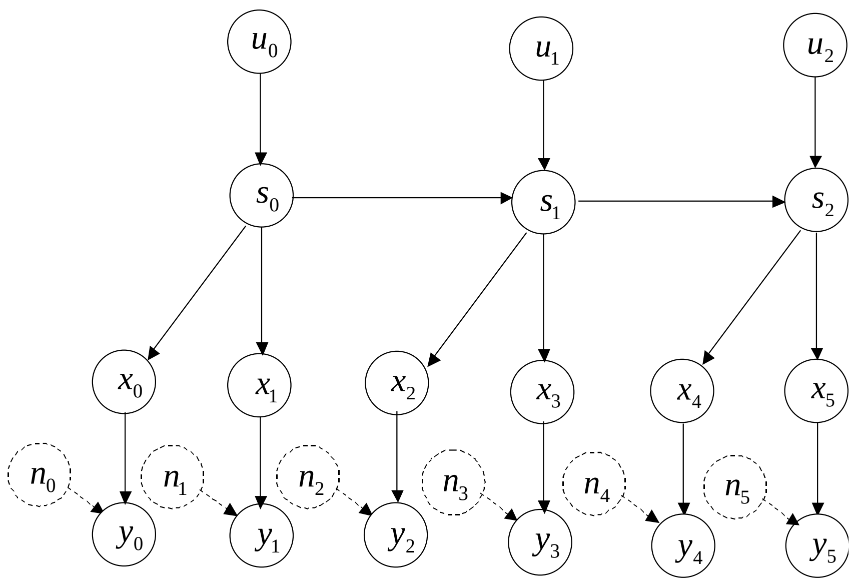

Figure 5 Bayesian network for a non-systematic convolutional code

vector that maximizes the *a posteriori* probability instead of symbol-by-symbol MAP. Thus the corresponding soft detection problem is to calculate the probability distribution $p(\mathbf{u}|\mathbf{y})$. The dependency structure in Figure 4 means that the joint probability distribution $p(\mathbf{u},\mathbf{y})$ can be factored as

$$p(\mathbf{u},\mathbf{y}) = \prod_{k=0}^{2} p(u_k, y_k)\,. \tag{6}$$

This is in essence how also the sum-product algorithm calculates the distribution.

From Equation (6) by using the independence of y_k's it can also be seen that the *a posteriori* probability can be factored as $\prod p(u_k \mid y_k)$. Thus the maximization of the *a posteriori* probability can in fact be done component-wise and the $\mathbf{u}$ can be determined by finding each u_k that maximizes the corresponding component distribution $p(u_k \mid y_k)$. In the case of this simple example, this can of course seen also directly.In the previous example the soft detection algorithm was reduced to a trivial one. This was possible because the model was memoryless in the sense that the random variables at different sampling times were independent. In [Fre98] a more complex example is presented where convolutional channel coding is modeled using the Bayesian network shown in Figure 5. In the example, the information bits $\mathbf{u} = (u_0, u_1, u_2)^{\mathrm{T}}$ are passed to the convolutional encoder that produces the output bits $\mathbf{x} = (x_0, x_1, x_2, x_3, x_4, x_5)^{\mathrm{T}}$ and the state transition sequence $\mathbf{s} = (s_0, s_1, s_2)^{\mathrm{T}}$ by the code-dependent rules:

$$\begin{cases} s_i = g(s_{i-1}, u_i) \\ x_i = f(s_i) \end{cases}. \tag{7}$$

White Gaussian noise is then added to produce the received sequence $\mathbf{y} = (y_0, y_1, y_2, y_3, y_4, y_5)^{\mathrm{T}}$. In this case, the forward-backward algorithm is the Bahl, Cocke, Jelinek and Raviv (BCJR) algorithm [BCJ74] that is used as a component decoder to calculate the symbol-by-symbol *a posteriori* probabilities in iterative decoding of Turbo codes. This example is discussed further in Section 3.3.1.1 where the maximum likelihood sequence estimator for this system is considered.

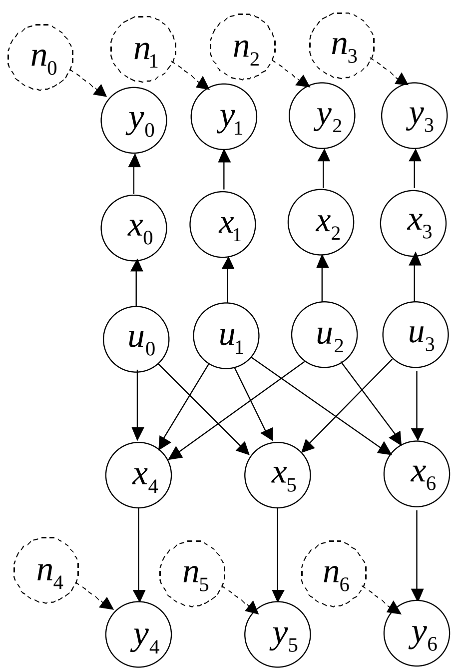

Figure 6 Bayesian network for a (7,4) Hamming code

When the network is more general, the conventional forward-backward algorithm cannot be applied. The forward-backward algorithm can be generalized to the sum-product algorithm [AjM00], [KFL01]. This algorithm can be used to compute probability distributions when the network is singly-connected, that is, any two vertices are connected only by a single path when edge directions are ignored. The sum-product algorithm is in fact also applicable for networks that are not singly-connected. However, in that case the algorithm does not produce the distributions precisely. In fact it is known, [Coo90], that the calculation of the probability distributions in general Bayesian networks is NP-hard. There is a strong body of evidence [MMC98], implying that the sum-product algorithm in multiply-connected graphs nevertheless produces good approximations of the distributions in many important application areas, in particular in the area of iterative channel decoding [SKL98], but the understanding of the behavior of the algorithm for multiply-connected graphs is still incomplete. See [FrM98] for a good overview on the subject. The iterative algorithms are discussed further in Section 3.3.2.

In [FrM98] an example is given where a (7,4) Hamming code is considered. This code takes 4 input bits and outputs these bits together with three parity bits $x_4 = u_0 \oplus u_1 \oplus u_2$, $x_5 = u_0 \oplus u_1 \oplus u_3$ and $x_6 = u_1 \oplus u_2 \oplus u_3$. The coded bits are transmitted through an AWGN channel using BPSK modulation. The corresponding Bayesian network is shown in Figure 6. It is clearly not singly-connected (e.g. the loop $u_0 \to x_4 \to u_1 \to x_5 \to u_0$). Due to the simple nature of the code, even the exact symbol-by-symbol *a posteriori* probabilities can be calculated. In [FrM98], a performance comparison between the MAP decoders that use the exact symbol-by-symbol *a posteriori* probabilities and decoders that use *a posteriori* probability estimates calculated by a sum-product algorithm on the network in Figure 6 are done. At 10^{-3} BER, the performance loss of the sum-product algorithm is about 0.25dB. It should be mentioned here that other methods can be used for calculating the probability distributions in multiply-connected Bayesian networks, such as Gibbs sampling [Pea88], variational inference [SJJ96] and Helmholtz machines [DHN95]. They are not typically used in detection and decoding applications and are thus outside the scope of this thesis.

3.3.1 Hard Sequence Detection

In this section we describe how a reduced complexity approach can be used in sequence detection, that is, in detectors where the entire information vector is detected simultaneously. The soft sequence detection is not considered mainly because the calculation of probabilities for all possible sequences is usually not feasible in practice. This is why the symbol probabilities are usually used in soft decoding. Although the sum-product algorithm is not directly applicable for sequence probability calculations we still use Bayesian networks when describing the calculation of probability distributions. This is done for the consistency of the presentation. For sequence estimation, the complexity reduction is done through the use of dynamic programming following the approach in [KaP98].

The specific methods considered in this section are the maximum-likelihood (ML) detection and linear detection. Applications such as the Viterbi algorithm for detecting convolutionally encoded data transmitted over memoryless channels [Omu69], [Vit67], maximum likelihood sequence estimator (MLSE) for equalizing linearly dispersive channels [For72] and multiuser detector (MUD) for demodulating non-orthogonally multiplexed data [Ver86], [Ver98] are discussed as examples.

3.3.1.1 Maximum-Likelihood Detection

Given the observed vector **y** in some system model, the maximum likelihood sequence detection of some unknown information vector **u** means solving the optimization problem:

$$\hat{\mathbf{u}} = \max_{\mathbf{u} \in U} p(\mathbf{y} \mid \mathbf{u}). \tag{8}$$

The complexity of solving (8) by brute force (e.g. by exhaustive search) is proportional to the number of possible information vectors, that is the cardinality |U|. However, with a suitable probabilistic structure of the problem, the complexity can be reduced substantially by using dynamic programming.

Our first example considers a convolutional decoder. Consider again the Bayesian network for convolutional channel coding shown in Figure 5. Recall the notation, where the information bits $\mathbf{u} = (u_0, u_1, u_2)^{\mathrm{T}}$ were passed to the convolutional encoder that produced the output bits $\mathbf{x} = (x_0, x_1, x_2, x_3, x_4, x_5)^{\mathrm{T}}$ and the state transition sequence $\mathbf{s} = (s_0, s_1, s_2)^{\mathrm{T}}$. White Gaussian noise was subsequently added to produce the received sequence $\mathbf{y} = (y_0, y_1, y_2, y_3, y_4, y_5)^{\mathrm{T}}$.

At the receiver we want to maximize the likelihood $p(\mathbf{y} \mid \mathbf{u})$. The dependence structure in Figure 5 implies that the joint probability distribution can be factored as

$$p(\mathbf{u}, \mathbf{s}, \mathbf{x}, \mathbf{y}) = p(\mathbf{u}, \mathbf{s}, \mathbf{x})\, p(\mathbf{y} \mid \mathbf{u}, \mathbf{s}, \mathbf{x}) \tag{9}$$

$$= p(\mathbf{u},\mathbf{s},\mathbf{x})\, p(\mathbf{y} \mid \mathbf{x}),$$

where the last equality applies, because, as is evident from the graph, given the transmitted codeword **x** the received vector **y** is independent of the state vector **s** and the information vector **u**. From (9) we obtain after some simplifications

$$p(\mathbf{y} \mid \mathbf{u}) = \sum_{\mathbf{x} \in X} p(\mathbf{y} \mid \mathbf{x})\, p(\mathbf{x} \mid \mathbf{u})\,. \tag{10}$$

Note that **x** is in fact uniquely determined by **u** and thus only one term in the summation is different from zero. Thus by denoting $\mathbf{x} = \Phi(\mathbf{u})$ the output of the encoder with input **u** we get

$$p(\mathbf{y} \mid \mathbf{u}) = p(\mathbf{y} \mid \Phi(\mathbf{u})) = p(\mathbf{y} \mid \mathbf{x}). \tag{11}$$

So far we have not utilized the memoryless property of the channel. This property is in fact indicated in the Bayesian network in Figure 5 where the different received bits y_k are only connected via the state variables. Thus given the transmitted codeword $\mathbf{x} = \Phi(\mathbf{u})$**,** which determines the state transition sequence the components y_k of the receiver vector **y** are independent. Thus Equation (11) can be factored and by adopting the log-notation we obtain the well-known decision rule

$$\hat{\mathbf{u}} = \max_{\mathbf{u} \in U} \sum_{n=1}^{N} \ln p(y_n \mid \Phi(\mathbf{u})_{\mathbf{n}})\,. \tag{12}$$

Due to the state structure of the system model, dynamic programming can be applied to this problem, resulting in the Viterbi algorithm. As a summary the dependency structure of the system was used explicitly twice to get Equation (12) and once implicitly to allow for dynamic programming to be used.

Our next example is the maximum-likelihood sequence estimator (MLSE) for linearly dispersive intersymbol-interference channels. In this example the transmitted information bits $\mathbf{u} = (u_0, u_1, u_2)^{\mathrm{T}}$ are distorted when transmitted through the channel which is modeled by the channel matrix **H**. The channel thus creates inter-symbol interference. The received vector $\mathbf{y} = (y_0, y_1, y_2)^{\mathrm{T}}$ consists of these distorted bits further degraded by additive white Gaussian noise:

$$\mathbf{y} = \mathbf{H}\mathbf{u} + \mathbf{n}\,. \tag{13}$$

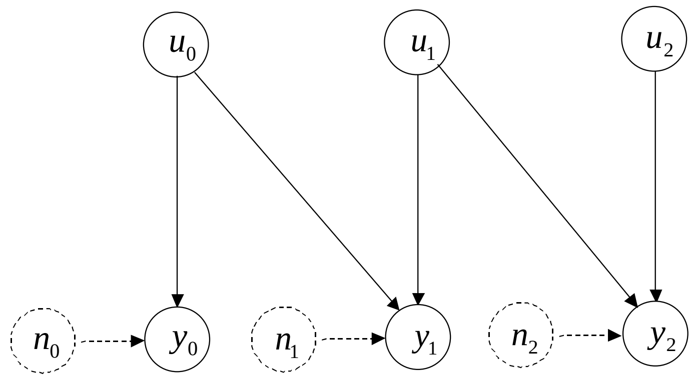

Figure 7 Bayesian network for a simple channel with ISI between the consecutive symbols

Figure 7 shows the Bayesian network for a simple ISI channel with such a short delay spread that there is intersymbol interference (ISI) only between the consecutive symbols. The channel matrix is not explicitly shown in Figure 7, since the channel coefficients are modeled in this case as deterministic variables and only random variables of the model are shown in Bayesian networks. They are however implicitly contained in the graph in the conditional PDFs $p(y_i \mid \mathbf{u})$. See Section 5.1 for a model where channel coefficients are modeled as random variables.

Although the probability distribution $p(\mathbf{y} \mid \mathbf{u})$ for Figure 7 can be calculated rather easily, the derivation of general algorithm based on the presentation of the figure is not simple. One option is to modify the Bayesian network by introducing artificial state variables that are used to present the channel state, that is the symbols transmitted in the past. This leads to a Bayesian network similar to that of Figure 5 and the resulting algorithm is the Viterbi equalizer. The complexity depends on the maximum delay spread of the channel.

In this example it is also straightforward to use the linear system model (13) to derive the MLSE in the conventional way. In this case we get

$$p(\mathbf{y} \mid \mathbf{u}) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{1}{2\sigma^2} (\mathbf{y} - \mathbf{Hu})^{\mathrm{T}} (\mathbf{y} - \mathbf{Hu}) \right) \tag{14}$$

and the problem may after some simplifications be reduced to maximizing

$$\Omega(\mathbf{u}) = 2\mathbf{u}^{\mathrm{T}}\mathbf{Hy} - \mathbf{u}^{\mathrm{T}}\mathbf{Ru}, \tag{15}$$

where $\mathbf{R} = \mathbf{H}^{\mathrm{T}}\mathbf{H}$. This optimization problem is NP-complete and thus offers little improvement in complexity over exhaustive search. However, since the maximal delay spread is in practice limited, **H** is a banded matrix and the complexity of the algorithm is substantially reduced. More details can be found in [KaP98], where also the detailed complexity reduction reasoning can be found. It is interesting to note that even this alternative reasoning uses artificial channel state variables that contain the past information bits.

As a last example we consider the optimum multiuser detection (in the maximum-likelihood sense). The derivation and analysis of the optimum multiuser receiver has been done by Verdù [Ver86] in the early eighties, when it was realized that the performance of the conventional detector can be exceeded, if the detection is done jointly for all users. For a K-user basic synchronous channel, the decision rule is to select $\mathbf{u} = (u_1, \ldots, u_K)^{\mathrm{T}}$ that maximizes

$$\Omega(\mathbf{u}) = 2\mathbf{u}^{\mathrm{T}}\mathbf{A}\mathbf{u} - \mathbf{u}^{\mathrm{T}}\mathbf{H}\mathbf{u}\,, \tag{16}$$

where $\mathbf{H} = \mathbf{ARA}$ is the unnormalized cross-correlation matrix. However, in this case the above complexity reduction method cannot be used, essentially since **H** is not a banded matrix. In fact it is known ([Ver89]) that the existence of an algorithm whose computational complexity is polynomial (w.r.t K) would imply that a polynomial algorithm exists for the famous traveling salesman problem. Thus the maximization of (16) can be solved with an algorithm whose time complexity per bit is $O(2^K / K)$ and no better algorithm is known.

3.3.1.2 Linear Detection

In this section we will briefly review the linear sequence detectors: decorrelating or zero-forcing detector and minimum-mean-squared-error (MMSE) detector. This review is used in Chapter 4 when reviewing the coded multiuser receivers.

One common way (see e.g [KaP98]) to derive reduced complexity is to look at a system model presented as a linear system

$$\mathbf{y} = \mathbf{H}\mathbf{u} + \mathbf{n} \tag{17}$$

instead of the probabilistic structure and furthermore to restrict the possible detectors (for the binary case) to be of the form

$$\hat{\mathbf{u}} = \mathrm{sgn}(\mathbf{z}), \tag{18}$$

where

$$\mathbf{z} = \mathbf{M}\mathbf{y} \tag{19}$$

and **M** is an arbitrary matrix. Such detectors are known as *linear detectors*. Using (17), we can write (19) as

$$\mathbf{z} = \mathbf{u} + \mathbf{n} + (\mathbf{MH} - \mathbf{I})\mathbf{u} + (\mathbf{M} - \mathbf{I})\mathbf{n}, \tag{20}$$

where **I** is the identity matrix. Thus the vector **z** is a composition of four terms: the desired signal **u**, the irreducible noise **n,** the structured interference (**MR-I**)**u**, and the residual noise (**M-I**)**n**. Note that only the latter two terms can be controlled by the choice of **M**. Setting **M**=**I** removes the residual noise term and the resulting detector becomes the symbol-by-symbol matched filter detector. This detector is optimal when **H** is a diagonal matrix, but in the general case it suffers from the structured interference, which, depending on the system that is modeled, can be for instance inter-symbol or multiple access interference. Alternatively, by choosing $\mathbf{M} = \mathbf{H}^{-1}$, we get a zero-forcing detector, which drives the structured interference term to zero. This is also known as the *zero-forcing equalizer* in the context of inter-symbol interference channel and as the *decorrelating detector* in the context of multiuser detection.

Although the zero-forcing detector is optimal in the maximum-likelihood sense, it has the undesirable feature of noise enhancement due to the introduction of a residual noise term. An alternative detector between the previous two extremes can be derived by selecting **M** which minimizes the quadratic mean $E(|\mathbf{u} - \mathbf{z}|^2)$. This *minimum-mean-square-error (MMSE) detector* is given by [Pro95]

$$\mathbf{M} = \left(\mathbf{H} + \sigma^2\mathbf{I}\right)^{-1}. \tag{21}$$

In this section we have briefly shown, how the classical reduced complexity (hard) sequence detectors can be derived by considering the stochastic structure of the system. For reference we have also discussed linear methods. All of these methods are basic textbook material although the Bayesian network approach is not commonly used. In the next section we use again the Bayesian network approach to review a more recently discovered class of reduced complexity sequence detectors: the iterative detectors.

3.3.2 Iterative Sequence Detection Methods

In the beginning of Section 3.3 we discussed the symbol-by-symbol MAP decoding when the problem has a natural multiply-connected structure. In this section we give practical examples and describe how iterative methods can be successfully applied for such problems. A first example is the optimum multiuser detection for convolutionally coded CDMA systems considered in [GiW96]. The dependency graph for that problem is shown in Figure 8 for the two-user case. There are several “loops” in the graph and thus the exact probability distributions cannot be calculated with probability propagation methods. In fact, as with the multiply connected problems in general, this problem also results in a solution with exponential computational complexity, which makes it impractical. As calculated in [GiW96], the time complexity per decoded bit for multiuser MLSE is $O(2^{WK})$, where W is the constraint length for the convolutional coding used in the system and K is the number of users. For instance, for a realistic 16-user case using the convolutional coding typically used in WCDMA systems with W=9, the number of the states in the joint trellis is 2^{143} and the time complexity per decoded bit is 2^{144}.

Naturally, there are many ways to produce suboptimal solutions to these kinds of problems. From the Bayesian network perspective, a most natural approach is to use some approximating algorithms for the computation of the probability distributions. These were briefly discussed in the beginning of Section 3.3. In this subsection we investigate more deeply the possibility of using the sum-product algorithm, which is exact for singly-connected graphs also for multiply connected graphs. Specifically, we study problems that produce Bayesian graphs that are multiply connected, but which allow execution of some efficient simplified version of the sum-product algorithm (e.g. allow the use of the forward-backward algorithm) in a number of separate parts of the network. The algorithm is executed in the different parts of the network either sequentially or in parallel and the connections between the parts are ignored during this. After the completion of the algorithms, the probability information is exchanged between the regions and the process is repeated. This approach is referred to as *iterative methods* in this thesis. A well-known example of these methods is the well-known Turbo decoding algorithm [Skl98].

Figure 9 shows the Bayesian network for a simplified Turbo code used as an example in [MeV98]. The close relation between the sum-product algorithm and Turbo decoding was recognized in [MMC98], where it was shown that turbo decoding can be viewed as an implementation of a calculation of *a posteriori* probabilities using the sum-product algorithm in which the presence of loops in the Bayesian network is ignored.

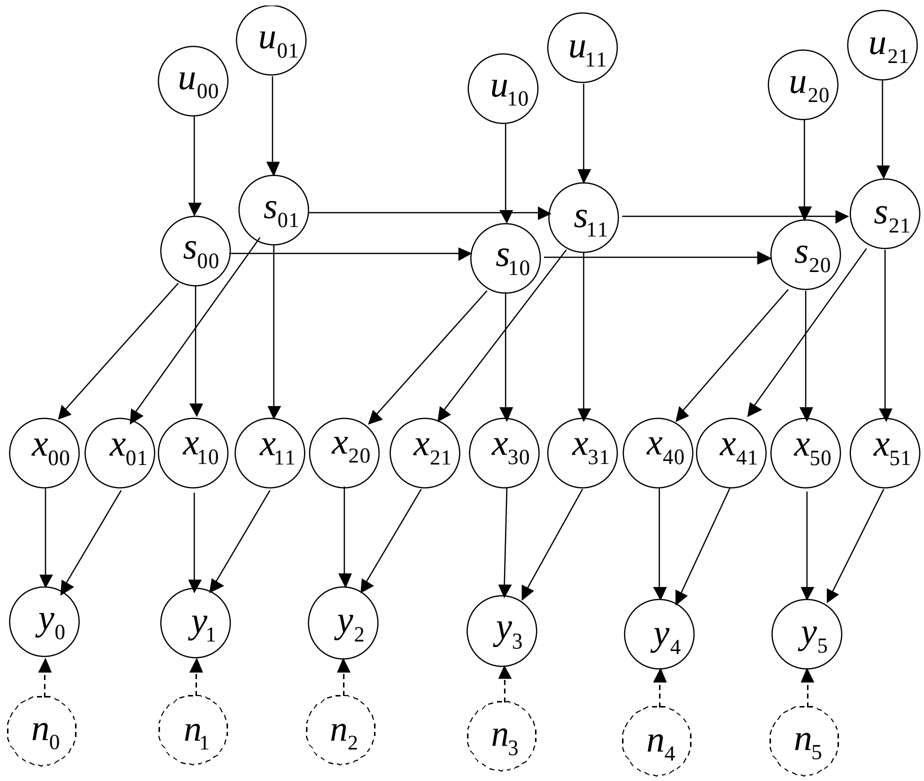

Figure 8 Bayesian network for coded multiuser detection with convolutional code and two users

They also show how this approach can be used to routinely derive several previously known iterative, but suboptimal, decoding algorithms for a number of different error-control systems, such as Gallager's low-density parity-check codes [Gal62], serially concatenated codes [BeM96], and product codes [HOP96]. Thus the Bayesian network approach provides a very attractive general methodology for devising low-complexity iterative decoding algorithms for hybrid coded systems. In Section 4 we show how this approach can also be applied to coded multiuser detection, where several proposed iterative algorithms can be understood through the use of Bayesian networks.

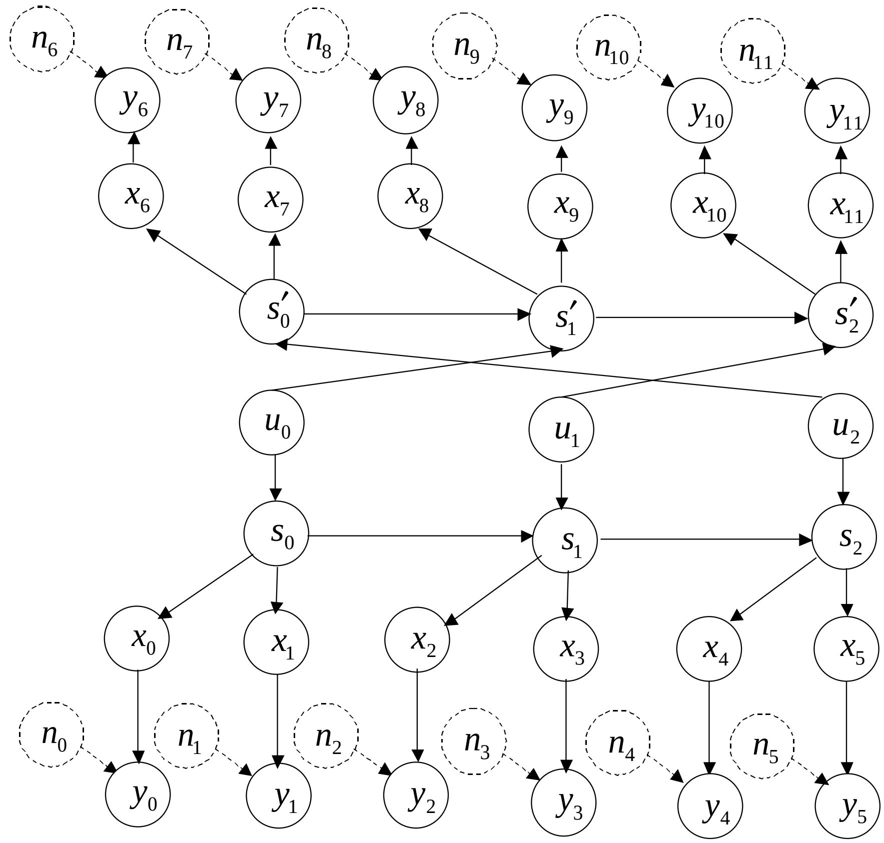

Figure 9 Bayesian network for a simple Turbo code in an AWGN channel

3.4 SOFT DETECTION AND DECODING IN WIDEBAND CDMA SYSTEMS

In this section we summarize the soft detection and decoding applications that are relevant in wideband CDMA systems. In current 3GPP wideband CDMA systems, the soft detection and decoding methods are used primarily in functions related to channel decoding. Both Turbo codes and convolutional codes are used, and convolutional codes may be used either with RS coding as a concatenated code, or as a stand-alone coding for services such as speech [3GPPc]. It is well known that the use of soft decision decoding can offer a significant performance gain in fading channels [Pro95, p.813], and it is thus typically applied when convolutional code is used either as stand-alone code or as an inner code of a concatenated coding scheme. This is a very simple application of soft detection. When Turbo codes are used, some iterative decoder algorithm is used in the receiver, which also utilizes soft decoding.

Looking at longer-term developments and the state-of-the-art research, the most extensively studied soft detection and decoding application for wideband CDMA systems is the iterative reception for coded multiuser detection that is discussed more extensively in Chapter 4. Also other studies addressing the soft detection and decoding in wideband CDMA systems have been done.

In [LiL00], an iterative PDF estimation and decoding scheme based on non-parametric PDF estimation is proposed for CDMA systems when the global noise is non-Gaussian distributed, as is the case with only a small number of high-power interfering users. In [HaA96], a decoder structure for concatenated codes is proposed that uses soft outputs produced by the inner stages of the receiver as compared to the standard approach, where hard outputs are produced by the inner stages. In [RaA97] the optimum metric for soft decision decoding with channel state information in the presence of fading is derived and the performance gains achieved with this are demonstrated. In [Nag98] a receiver with an iterative soft decision using forward-error-corrected data is proposed. This utilizes a soft-decision Viterbi decoder preceded with a soft-decision processor, which obtains feedback info from the decoder output.

One can also utilize soft detection to produce improved soft output CDMA detectors that provide input for soft decision decoders. This approach is discussed in detail in Chapter 5.

In this thesis we study two different applications of soft detection and decoding for wideband CDMA systems. The use of iterative receivers for coded multiuser detection is a long-term possibility, because the receiver complexity is still substantial. This will be the main topic of Section 4. In mobile stations, the processing power and power consumption constraints are still more stringent and thus more attention must be paid to the algorithm complexity. Thus in Section 5 we study the soft-detection problem of producing the correct soft information for soft-decision decoding of a convolutional code by using a RAKE-like soft detector.

4 CODED MULTIUSER RECEIVERS

In this chapter we review coded multiuser receivers and show how Bayesian networks can also be applied to understand iterative joint receivers for coded CDMA systems. When interfering users are present in a CDMA system, the total interference power, although spread over the whole bandwidth, steadily increases. With a simple matched filter (MF) receiver this causes a gradual increase of the symbol error rate. The performance loss is more severe if the interfering users are using higher transmitting powers than the desired user. This phenomenon is called the *near-far problem*. It was first recognized and solved by Verdú [Ver86], by proposing that the symbols of all the users should be detected simultaneously. However, as was discussed in Section 3.3.2, this original (optimal) receiver structure was prohibitively complex and thus suboptimal approaches were needed. The research of *multiuser receivers* that detect the symbols of all the users simultaneously has grown since Verdú's original article into a whole research branch.

There are also ways to further extend the idea of joint detection. Since all practical systems employ some channel coding to improve the performance, one could argue that the optimum joint receiver should jointly detect and decode the information streams of all users. Clearly, this is an even more complex task to be carried out in practice, but again some suboptimal algorithms can provide the desirable tradeoff between the performance gain and complexity. The work on this research area has been active during the last years and the articles [P1, P2] in this thesis are part of this research.

The detailed content of this chapter is as follows. In Section 4.1 we will deviate slightly from the main theme and describe how the channel coding should in fact be integrated with the spreading for the maximum performance gain. This approach is presented to give some perspective when investigating the main subject of the chapter, namely, how soft detection and decoding methods may be used to achieve a closer connection with channel decoder and multiuser detection for a good performance gain when separate spreading and channel coding are used. In the rest of the chapter, multiuser receivers for coded CDMA systems are presented based on the classification given in [GWi96].

The broad class of multiuser receiver architectures which treat multiuser detection and channel decoding separately are referred to as partitioned multiuser receivers and are discussed in Section 4.2. The drawback with the partitioned approach is that since the multiuser detection operates at the code symbol level as though there were no coding in the link, it will not derive any advantage from the coding. This drawback can be avoided with a tighter integration between the multiuser detection and decoding. In Section 4.3 we will review the existing research on such integrated receiver architectures. Our emphasis in this thesis is on the iterative joint multiuser receivers, which are reviewed in depth in Section 4.3.3.

4.1 COMBINED CHANNEL CODING AND SPREADING

The code rate can be defined as the ratio of the information bits to the code bits. Any non-trivial channel code has a code rate $Q<1$. Assuming that a fixed information bit rate is required, the encoding increases the signal bandwidth by spreading it with a factor of $R=1/Q$. Usually, this spreading is kept as small as possible to save bandwidth. However, in DS-CDMA systems the signal spreading is desirable and the spreading process can be considered as a low-rate code, which is simply a repetition code followed by a multiplication with the spreading code. This suggests that, instead of a high rate channel code followed by separate spreading, a performance gain could be achieved by using a low rate channel coding that would also perform the spreading with the spreading factor $R=1/Q$, where $Q<<1$ is the code rate. This approach was first proposed and analyzed in [Vit90]. There a very low rate convolutional code is used as a channel code. The encoder output rate is equal to the chip rate and thus no further spreading is required. The encoder output is multiplied with a pseudo-random scrambling sequence in both the quadrature and in-phase branches.

The analysis in [Vit90] shows that the total capacity of a CDMA system using combined coding and spreading asymptotically approaches the Shannon limit in the AWGN channel. It is not a surprise from the information theoretic point of view, but since these kinds of systems are expected to be implementable in practice at least in the long-term, this is an important result.

4.2 PARTITIONED MULTIUSER RECEIVERS

When designing a multiuser receiver architecture for a coded CDMA system, a simple approach is to consider multiuser detection and channel decoding separately. This class of multiuser receiver architectures is referred to as *partitioned multiuser receivers*. One can take any of the uncoded multiuser receivers followed by a channel decoder. If the particular multiuser receiver produces hard decisions, hard decision decoding must be used which causes some loss of performance. This is called the *hard decision approach*. The hard decision case is analyzed in [GWi96] and can be used mainly as a reference point. The performance of the hard decision multistage IC followed by a channel decoder is analyzed in [JuK99].

Alternatively, one can design multiuser detectors that provide soft decisions. This is called the *soft decision approach*. In this case the soft decision decoding can be utilized separately for each user. The soft decision approach is also analyzed in [GWi96] for a conventional single-user soft-decision receiver and for a soft-output decorrelating detector. In addition, the paper contains a brief discussion on trellis-based soft-output multiuser detectors and on soft-output multistage detection. It should be emphasized that, in the partitioned approach, the tentative decisions in the multistage detection do not utilize the channel code information. The multistage detection using channel code in tentative detection is discussed in Section 4.3.

Other linear soft-decision multiuser receivers are considered in [Ale97], [SRA96] and [SAR98], where a soft-output decorrelating receiver (See section 3.3.1.2) is studied and a new kind of linear receiver, called the projection receiver, is proposed. The projective receiver achieves interference cancellation by projecting the undesired users onto the space spanned by the desired users' signal vectors. The detector calculates the least-squares estimate of the interfering users' data that is used to yield the soft output. A computationally efficient adaptive version of the algorithm is proposed in [ScM97] and [SAR97].

In [VSP97], a soft-output Maximum *A Posteriori* (MAP) detector is used to provide optimum sequence of soft inputs to the disjoint channel decoders of the users. In [HaS97], the soft-output multiuser detection algorithms are based on the algorithms developed for channels with ISI. This leads to a derivation of an optimum soft-output multiuser estimation (OSOME) algorithm and a reduced complexity suboptimal version (SSOME). Another trellis-based partitioned receiver for an asynchronous CDMA system is proposed in [NSR98], where a modified reduced-complexity recursive detector (RCRD) is used as a soft-output multiuser detector followed by a bank of Viterbi decoders, one for each user.

4.3 INTEGRATED MULTIUSER RECEIVERS

Since all the partitioned multiuser receivers operate at the code symbol level as if there were no coding on the link, there is no advantage taken from the coding in the actual multiuser detection phase. This causes a performance loss. This can be avoided by integrating the multiuser detection and channel decoding more tightly.

4.3.1 Optimal Multiuser Receiver for Coded CDMA Systems

In [GiW96], the optimal multiuser sequence estimator is formulated for a coded DS-CDMA system in a non-dispersive additive white Gaussian noise channel. The receiver thus performs multiuser detection and channel decoding together by using a Viterbi algorithm, which in the case of a rate-1/2 code is operating on a trellis with 2^{WK-1} states and two branches per state, where K is the number of users and W is the constraint length of the convolutional code. The number of the states clearly grows very fast with both K and W. In fact, even a simple four-user example with a four-state rate-1/2 convolutional code (W=3) requires a trellis with 2048 states! Thus the optimal multiuser sequence estimation is prohibitively complex for a real system. It does however provide a good reference point by which to judge the suboptimal receivers. In [GWi96] the use of some sub-optimum trellis-based algorithm using for instance reduced trellis or sequential decoding is proposed to reduce the complexity.

For CDMA systems using trellis-based modulation and coding, an optimal multiuser receiver was proposed in [FaA96]. They also proposed a sub-optimum detector based on a reduced tree search algorithm and a multistage IC receiver.

4.3.2 Interference Cancellation with Hard Decoded Tentative Decisions

In decision-directed multiuser receivers such as successive IC and multistage IC receivers, the coding information can be included very naturally in the receiver structure by using the channel decoder output as tentative decisions. This general approach is proposed and analyzed already in [GWi96], where a soft decision Viterbi algorithm is proposed for tentative decision generation in a multistage IC receiver. The performance of such a receiver is analyzed in [JuK99]. Also the use of partial interference cancellation in combination of joint decoding is studied there.

In [RKS97], a joint successive interference cancellation scheme is proposed, where hard or soft decision Viterbi decoding is used in each step of the interference cancellation. In [BrY98], an improved method is proposed, where several hypotheses are maintained in each user's Viterbi decoder until several lower-power users have been decoded.

The approach presented above can also be applied to multistage IC receivers. In [DaE98] and [DEA98] soft-decision decoding is used for tentative decisions in a multistage IC receiver to reduce the complexity of the joint detection and decoding scheme. Suboptimal channel decoding is also used to further reduce the complexity. In [HaL98] and [HLi98] soft-decision decoding is used for tentative decisions in a multiuser detector that is additionally using a sliding-windowbased approach to cancel the multiuser interference. In [HaL99], a modified version of the receiver structure is proposed that effectively combines the RAKE receiver with the joint multiuser receiver and decoder proposed earlier.

As was mentioned previously, a multistage IC receiver that uses decoded tentative decisions is proposed for CDMA systems using a trellis-based modulation and coding scheme in [FaA96].

One main difficulty with using decoded tentative decisions in interference cancellation in fading channels is that, if fading is slow compared to the data rate, a large interleaving block-size is required to provide sufficient coding gain, if the normal channel code is also used for tentative decisions. In this case, the additional de-interleaving and re-interleaving required causes an unacceptably long delay in the cancellation process. There are also some significant system impacts of this delay in wideband CDMA systems, which are discussed in 4.3.4. [SaN96] and [SaW96] propose this kind of system using multi-carrier modulation where no interleaving is required. They also use the regenerative or chip level interference cancellation, where the interference cancellation is performed at each stage for the spread signal.

Some other decision-directed receivers for coded systems have also been proposed. A minimum-mean-squared-error decision-feedback (MMSE DF) multiuser receiver for coded CDMA systems is proposed in [MVF99]. A single stage decision-feedback multiuser detector (DFMD) using soft decision Viterbi decoder is proposed in [HaS96].

4.3.3 Iterative Joint Multiuser Receivers

The receivers described in the previous section use hard decoder outputs for tentative decisions. The only exception is the receiver proposed in [BrY98], where several hypotheses are maintained. By using soft output decoders, a performance gain may be achieved by using soft information for the interference cancellation. In the related literature, the interference cancellation receivers with soft tentative decisions are usually called *iterative joint multiuser receivers*. This name probably comes from the use of soft-input-soft-output (SISO) decoders in a manner similar to that of the iterative decoding schemes such as the decoding of Turbo codes. These algorithms are typically derived from iterative decoding schemes in an essentially ad hoc manner. In our context, these methods can be understood by looking at the corresponding Bayesian network. Figure 10 shows the Bayesian network for a simple convolutionally coded synchronous CDMA system already discussed in Section 3.3.2. Assuming that the incoming distributions are known, then any variant of the forward-backward algorithm such as the MAP algorithm (or the max-log-MAP) can be applied by the SISO decoders (one for each user to be decoded) operating on the frame part of the network. The key remaining issue is how the soft information is exchanged between the individual SISO decoders. Different papers propose different methods for this information exchange. A similar approach can be taken in asynchronous and Turbo-coded CDMA systems, but the network will be more cumbersome.

In [WaP98] and [WaP99] SISO decoders are used both for multiuser detection and for channel decoding in an iterative manner for convolutionally coded CDMA systems. A synchronous CDMA system is considered in [WaP98] and this is extended to asynchronous CDMA systems in [WaP99]. In these papers the exact multiuser SISO and two alternative low-complexity algorithms are proposed that are based on soft interference cancellation and on linear MMSE filtering. In [ARA99], a similar receiver structure is analyzed for a large number of users (compared to the processing gain) in a convolutionally coded asynchronous CDMA system and a near-single user performance is reported. In [Moh97], [Moh98], [Moh98b] and [MoG98] a slightly different structure for an asynchronous CDMA system is studied which is derived from iterative methods used for minimizing cross-entropy. A reduced-complexity scheme using Log-MAP approximation of the exact MAP algorithm is proposed for convolutionally coded asynchronous CDMA systems in [VaW98]. In [ReA97], [RAA97], [Ral97] and [RSA98] a synchronous CDMA system in an AWGN channel is studied and still another approach is proposed where the decoder input metric is calculated in a reduced manner. The complexity of this approach is reduced in [Chi01] where a decision-feedback SISO multiuser detector is used. In [ZhB01] an iterative multiuser receiver for decoding Turbo-decoded synchronous CDMA signals is studied both for Gaussian and non-Gaussian impulse noise.

In [QTG00] an iterative interference cancellation receiver for asynchronous Turbo-coded CDMA is proposed. Expectation values of the coded bits are used as soft values in the interference cancellation step. This essentially means that the soft values are calculated by taking hyperbolic tangent of the log-likelihood ratios for the coded bits.

In [HsW01] a low complexity iterative multiuser receiver for Turbo-coded synchronous CDMA system is proposed. A modified decorrelating decision-feedback detector that uses given *a priori* log-likelihood-ratios to produce soft-output is proposed.

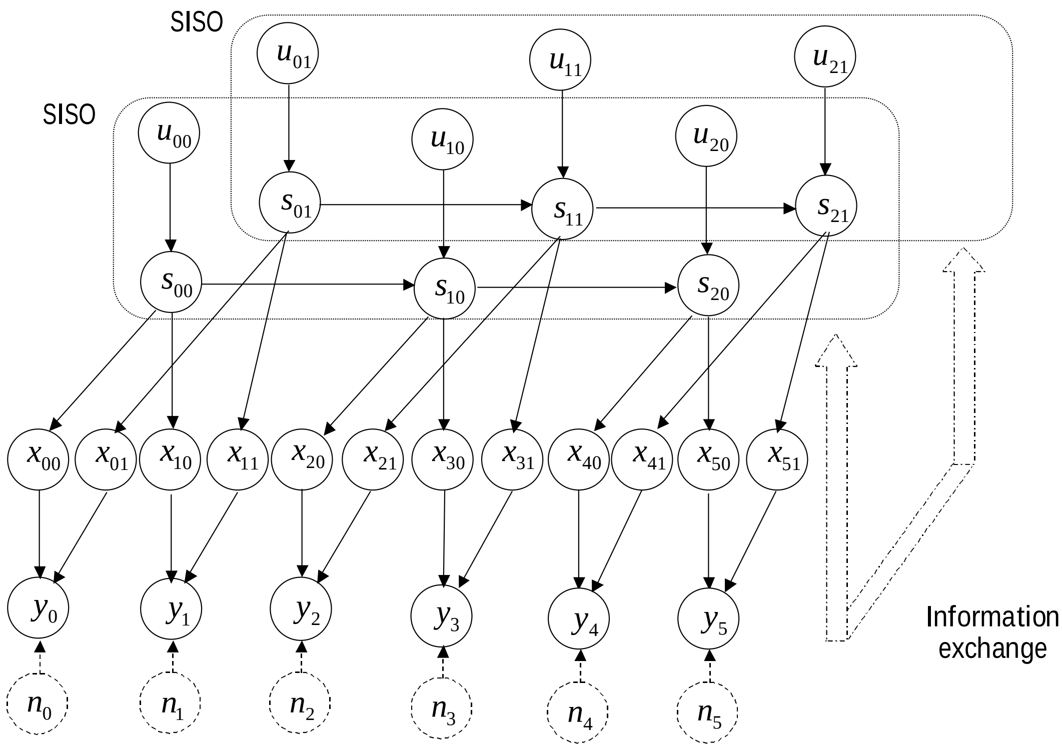

Figure 10 Generic message exchange principle for iterative joint multiuser receivers

In [HSH97], a multi-code CDMA system is studied and an iterative receiver using soft tentative decisions based on the SISO decoder output is proposed. The same kind of receiver was independently proposed in [P1] where it was compared with an optimal multiuser likelihood calculation algorithm developed in the same article. The work on the optimal multiuser likelihood calculation algorithm was continued in [P2], where the impact of the variance estimation algorithm was studied.

In [KaH97] the use of soft tentative decisions based on the SISO decoder output is studied for coded multi-carrier CDMA (MC-CDMA) systems. This is also studied in [AAA98] and in [AkA98]. In [Her98] the iterative cancellation of interference with the aid of soft values of the decoded bits is studied for multi-code CDMA systems. In [ThG01], a soft iterative multisensor array receiver for convolutionally coded asynchronous CDMA systems is proposed.

4.3.4 System Issues of Iterative Joint Multiuser Receivers

In addition to the increased complexity, the main difficulty with using iterative joint multiuser receivers - or IC receivers with decoded tentative decisions - in fading channels is the prohibitively long delay caused by the interleaved channel codes. Currently, interleaving is virtually always used in channel codes designed for fading channels because it is a relatively simple method to obtain the required time diversity. However, in order to obtain this time diversity, the interleaving block length must be substantially longer than the channel coherence time. On the other hand, the whole interleaving block must be received before the iterative detection/decoding process can take place. This means that there is a significant delay between the actual reception of the signal and the actual availability of the receiver symbol. This is naturally unacceptable for delay-sensitive applications.

However, even worse problems are caused by this delay to fast power control, which is used in wideband CDMA systems. The operation of the fast power control requires that the transmission power is adjusted based on the received power control (PC) bit. This needs to be done with a reasonably low delay. Thus the delay induced by the iterative joint detection/decoding is unacceptable high. There are two alternative solutions to this problem. In the first alternative one detects and decodes the power control bits with a conventional receiver. For instance in 3GPP WCDMA systems this is reasonably straightforward, since the power bits are transmitted in a separate physical control channel. Naturally the joint detection/decoding gain is not achieved for PC bits, which reduces the system performance. This approach is not studied further in this thesis.

The second alternative is to use a coding scheme that is a concatenation of an inner non-interleaved code and an outer interleaved code. Only the inner code would be used in the multiuser detection and the delay between the symbol reception and the availability of the detected symbols would be reduced. In [P3], an analysis is presented which shows that interleaving is not so significant for good *interference cancellation* performance even in correlated fading channels. In fact, in a correlated Rayleigh fading channel, the performance of an IC receiver using decoded tentative decisions and a relatively weak non-interleaved code will be near the single-user performance limit.

5 SOFT DETECTION AND DECODING IN MOBILE TERMINALS

In the previous chapter the use of soft detection and decoding methods was considered for the base station receiver. In the mobile terminal the complexity constraints are much harder and the use of advanced signal processing algorithms must be justified more carefully. In particular the limited processing power of a mobile terminal implies that the use of iterative methods considered for coded multiuser detection in Section 4 can only be justified if the achieved gains are sufficient. However, the downlink interference levels are in general much smaller than the uplink MAI and this imples less achievable gain in the downlink. Thus an approach is selected where the iterative methods are not studied, but instead the focus is on soft detection methods derived by modeling inter-symbol-interference as independent Gaussian noise. This approach can be seen a multipath variant of Gaussian approximation. It is shown that even with these moderate-complexity methods a significant gain is achieved compared to the conventional RAKE receiver.

In this chapter we review the use of these soft methods in mobile CDMA receivers. Although the original contributions [P4]-[P6] use Gaussian approximation and conventional analytic methods instead of the Bayesian networks, here we choose to use the Bayesian network approach to describe the problems. This is to achieve unified presentation, and to illustrate how these problems appear from the perspective of iterative methods. Wherever appropriate we point out some key issues related to applying iterative methods to these problems.

5.1 REDUCING THE COMPLEXITY IN SOFT DETECTION AND DECODING

Looking at RAKE-type receivers, which employ a bank of correlator fingers to utilize the multipath diversity, the filter bank outputs in the downlink of a WCDMA system are given by

$$y_i^{(l)} = \sum_{k=1}^{K}\sum_{j=1}^{N}\sum_{p=1}^{L}\rho(i,l,j,p,k)h_j^{(p)}x_{jk} \ , \tag{22}$$

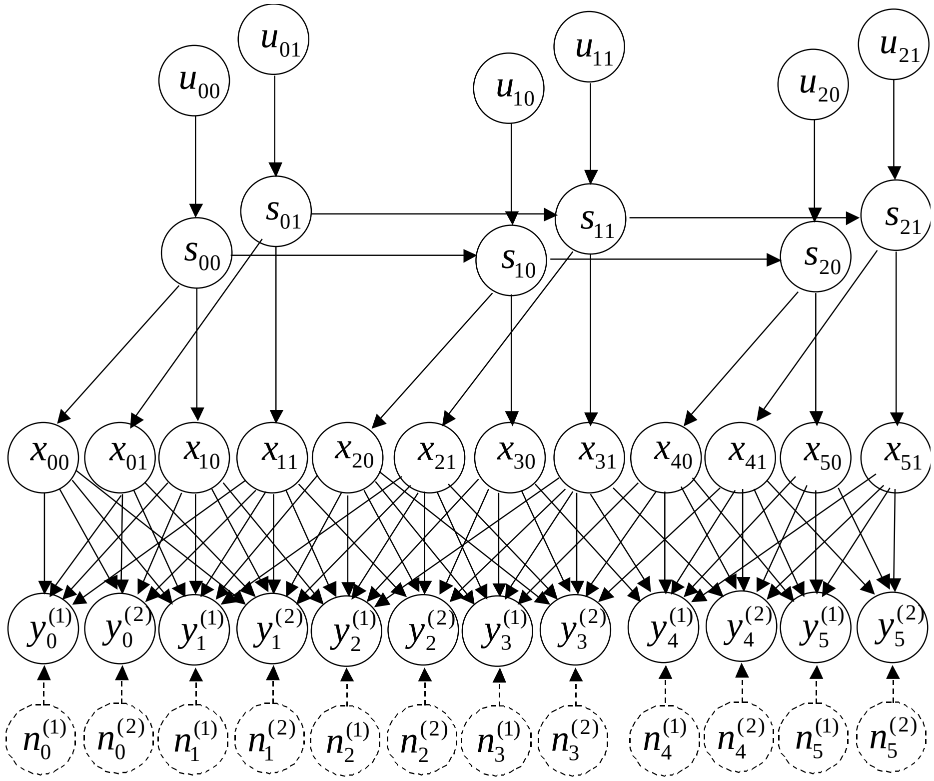

Figure 11 Bayesian network for CDMA downlink system model with two users and known channel coefficients

where $\rho(i,l,p,j,k)$ is the correlation between different symbols and users in different paths, $h_j^{(p)}$ are the channel coefficients for *p*th path, and x_{ik} is the coded information symbol for user *k* that is generated by some encoder e.g. via a state machine

$$\begin{cases} s_{ik} = g(s_{i-1,k}, u_{ik}) \\ x_{jk} = f(s_{ik}) \end{cases}. \tag{23}$$

As stated earlier, the detection and decoding problem for a mobile receiver in this context can be regarded as a problem of probabilistic inference in a Bayesian network. In the downlink with multipath propagation, the signals traveling via different paths are misaligned in time and *interpath interference* is introduced even when orthogonal codes are used for different users. Thus there is interference both between different users as well as between different symbols. The resulting Bayesian network is shown in Figure 11. For simplicity, the channel coefficients are assumed to be deterministic and thus not included in the Bayesian network. The case where channel coefficients are considered as random variables is discussed later. In this case however,

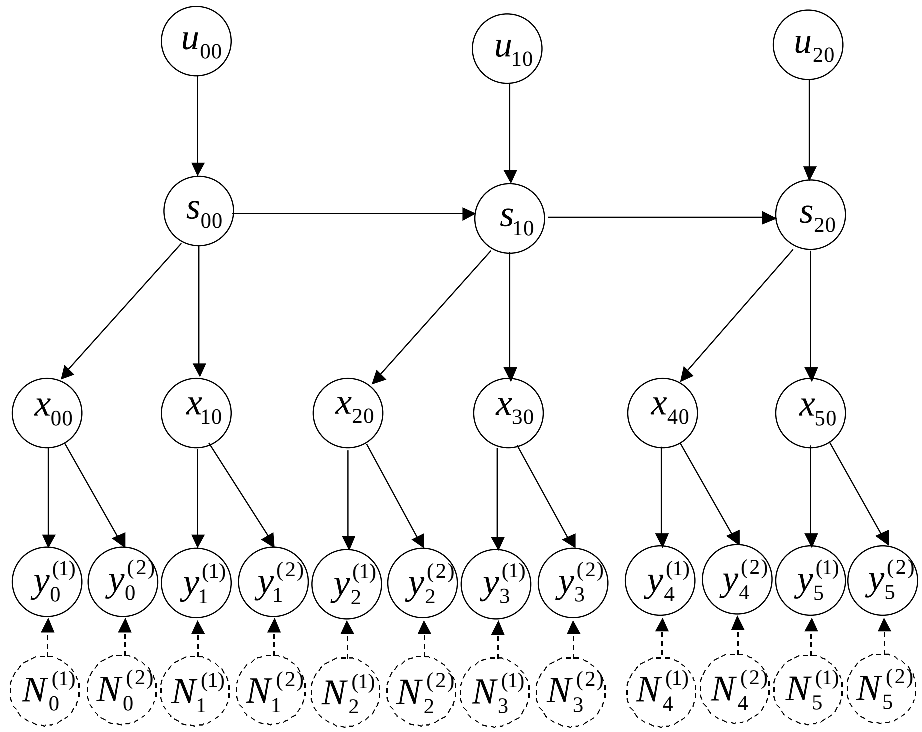

Figure 12 Bayesian network for a CDMA downlink model for one user when interference is modelled by Gaussian approximation and channel coefficients are known

the limited processing power of a mobile terminal does not allow the use of iterative methods considered for coded multiuser detection in Section 4, especially given the interference levels that are much smaller than for uplink MAI, which implies less achievable gain.

One alternative is to ignore the interdependencies between the subsequent symbols. The model is thus simplified to the one in Figure 12. As a result, the interpath interference is modeled as independent Gaussian interference. In fact this is a multi-path variant of the well-known Gaussian approximation. This approach may be used to derive improved RAKE receivers with moderate complexity.

In the previous discussion the channel coefficients have been assumed known for simplicity. Now we need to deal with those explicitly as random variables. Thus we add them in Figure 12, which results in the Bayesian network shown in Figure 13. Notice that the channel coefficients are assumed to be uncorrelated between different paths, but correlated in time. Although the resulting network looks relatively simple, it results in significant complexity increase when the sum-product algorithm is applied to the network. This is due to the fact that the channel coefficients are continuous-valued random variables while the other random variables in the network (with

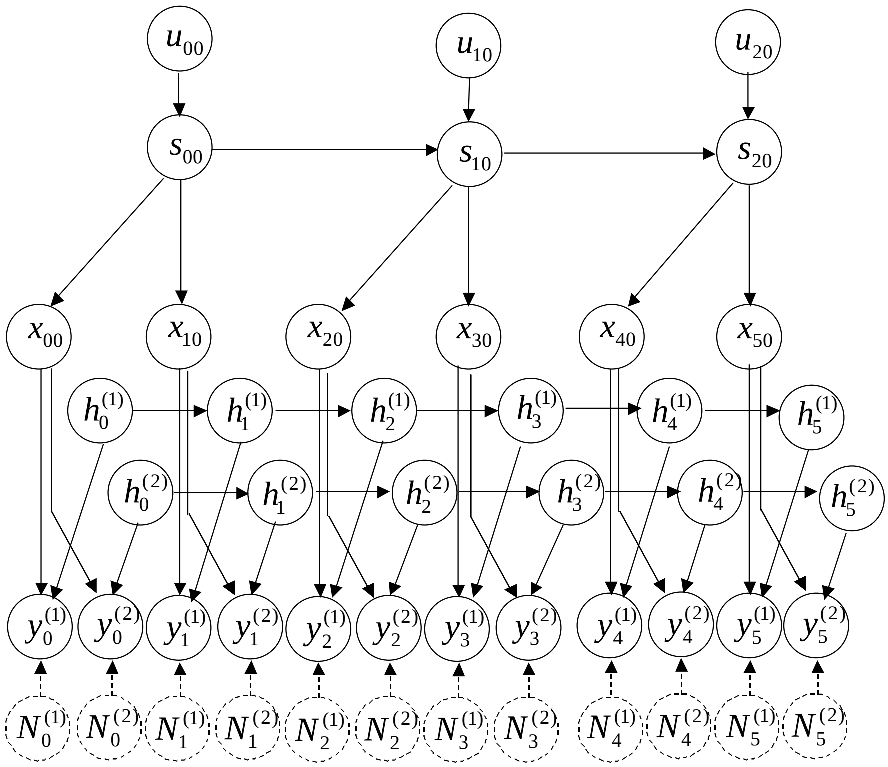

Figure 13 Bayesian network for a CDMA downlink model for one user when interference is modelled by Gaussian approximation and channel coefficients are unknown

the exception of the additive white Gaussian noise variables which are typically treated implicitly in the sum-product algorithm) are discrete valued.

This has a deep impact since the marginalisation step, which plays a key role in the sum-product algorithm, requires an integral to be calculated over random variables. For discrete random variables this reduces to a summation over the value range of the variable, but for continuous variables there is no simple way to do this. See [Fre98] for a review on sum-product algorithm in mixed networks containing both continuous- and discrete-valued random variables. Other approaches, which do not use Bayesian networks, can naturally also be applied, such as the blind linear equalization for CDMA downlink proposed in [SlG00].

It should be observed that for the continuous-valued random variables representing the channel noise and interference, these problems can be avoided by incorporating these variables into the matched filter outputs $y_i^{(l)}$. Thus the $y_i^{(l)}$'s become continuous-valued, but this does not cause the problems mentioned above, since these are the *observed* random variables. We will use a similar approach to deal with the channel coefficients. Furthermore we will assume perfect interleaving and subsequently assume that the channel coefficients are uncorrelated. This results in a Bayesian

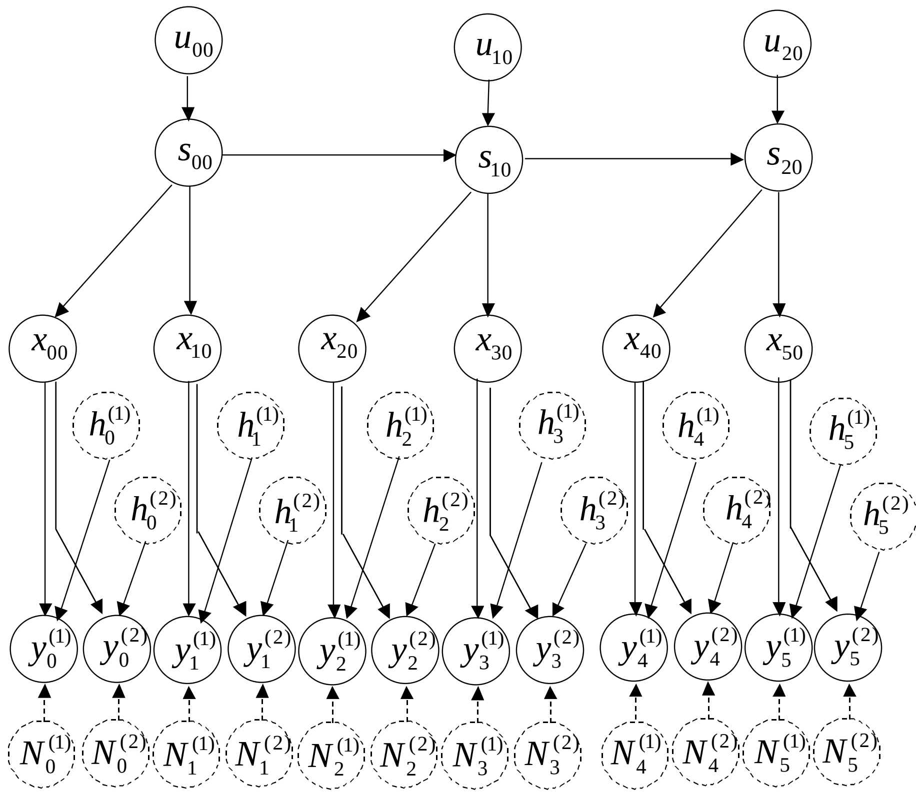

Figure 14 Bayesian network for a CDMA downlink model with perfect interleaving for one user when interference is modelled by Gaussian approximation and channel coefficients are unknown

network shown in Figure 14. It should be noted that this network is in fact singly-connected. Thus the sum-product algorithm is reduced to symbol metric generation followed by the application of a SISO decoder. If only hard decisions are required for information bits, the SISO decoder may be replaced with a soft decision Viterbi decoder. Thus the emphasis is on the symbol metric generation problem.

This approach of having a symbol metric generation followed by a Viterbi decoder has been used in the publications [P4]-[P6] to derive an improved RAKE receiver with a moderate complexity. In the next section we discuss these and other improver RAKE receivers that can be utilized in symbol metric generation for soft decoders.

5.2 SYMBOL METRIC GENERATION FOR SOFT DECISION DECODERS

In CDMA systems, the metric is usually generated from the output of the RAKE receiver ([Pro95]), where the signals propagating through different paths are received in individual fingers of the RAKE receiver. The outputs from these fingers are then coherently combined to provide the detected signal. The combining algorithm commonly used in CDMA RAKE receivers is the conventional maximal ratio combining (MRC) algorithm, which is known to produce maximal signal-to-noise ratio for diversity channels with equal noise powers and perfect channel estimates. However, when receiving a signal through a multipath channel from a base station, a large part of the noise in the RAKE finger output is due to the interference between the signals propagating through different paths [HHT97], [HJL99].

The original MRC combining scheme by Brennan can be extended in many ways to take this *inter-path-interference* into account. In [TSW00] both an optimum and suboptimum combining scheme for RAKE receivers in DS-CDMA systems are proposed. The optimum combining requires the inversion of the interference-plus-noise covariance matrix, while the suboptimal approach only utilizes noise and interferer powers. In [BOW00] a generalized RAKE receiver is proposed, where the weights are derived from a maximum likelihood formulation.

In the research constituting the second part of this thesis, methods similar to the suboptimal approach in [TSW00] are independently proposed. However, the derivations are performed in a different manner using the ideas presented in Section 5.1. This allows consideration of additional issues such as eventual channel estimation errors and non-constant amplitude modulation schemes. In the remainder of this section we shall briefly discuss the approach used.

Consider a RAKE receiver for a CDMA system. As was mentioned above, the actual noise power varies between the fingers depending on the multipath component magnitudes and the number of interfering users. This means that in practice different RAKE fingers have unequal interference powers and thus the metric derived from the conventional MRC output will not produce the correct path metrics for the maximum-likelihood decoder even if the interference is assumed to be Gaussian. On the other hand the original MRC algorithm derived by Brennan [Bre59] is optimal for combining diversity branches with Gaussian noise having unequal noise powers in different branches. In Brennan’s scheme, each combining weight is inversely proportional to the noise power of the diversity branch. Thus the implementation of this scheme requires estimates of these noise powers. In addition the channel estimation errors are not taken into account. Using the approach presented in Section 5.1 we can derive an improved RAKE receiver that takes all these issues into account. This was done in [P4], [P5] and [P6] without explicitly using the Bayesian network approach taken here.

Mobile systems are currently evolving to satisfy increasing demands on packet-data services, in particular the need for higher bit rates [NBK00], [FPR01]. In GSM for instance, the EDGE standardization is currently under development to provide faster packet-data services [3GPPb]. In the currently completed version (Release 99) of the wideband CDMA (WCDMA) specification, the technology used in the third generation mobile systems, high data rates are realized using low spreading factors, e.g. spreading factor G=4 for 2 Mbps data rate. Recently there have been many studies on the evolution of the WCDMA air interface beyond the original requirements, such as the high-speed downlink packet access (HSDPA), which is aiming at high peak data rates and low overall delays [PDF01], and which will be included in the next version (Release 5) of the specification [3GPPa]. The HSDPA utilizes fast link adaptation, where the modulation size and the rate of the channel encoder are adapted to track the variations of the radio channel. In practice the data will be transferred using a higher order modulation (e.g. QAM) and a smaller amount of channel encoding when the channel quality is good.

In order to obtain satisfactory performance with low spreading factors and high-order modulation schemes advanced CDMA receiver structures are needed. One way to improve the performance is to utilize the receiver structure using soft metric generation followed by a soft-decision decoder as discussed above. It is well known that the use of soft decision decoding can offer a significant performance gain in fading channels [Pro95, p. 813]. This approach is studied in detail in [P5].

6 SUMMARY OF PUBLICATIONS

This section gives a summary of the publications constituting this thesis. These publications result from research on soft detection and decoding. First part of the research focuses on coded multiuser detection in the CDMA base station and second part on the reception in a mobile terminal. Publications [P1], [P2] and [P3] contain the results of the research work related to the coded multiuser detection and are discussed in Section 6.1. Since none of these publications contains a general overview, we explain also the research work done in more detail. The second part of the research considers improved RAKE-based reception in the mobile terminal employing soft detection. Publications [P4], [P5] and [P6] contain the results of that research and are discussed in Section 6.2. Since Bayesian networks are not explicitly used in the publications, we describe here, how they were used in the development of the algorithms presented in the publications. The general approach was to develop the initial idea for the receiver structure using Bayesian networks, after which the detailed derivation of the various components in the receivers, such as the likelihood calculation algorithms, was done with other methods.

6.1 RECEIVERS USING ITERATIVE DECODING WITH INTERFERENCE CANCELLATION

The first part of this thesis consists of research studying the use of iterative receivers in coded multiuser detection. This research is reported in Publications [P1]-[P3]. The starting point for this research was to utilize methods that are used for Turbo decoding. The recently discovered connection between Turbo decoding and sum-product algorithm in Bayesian networks [MMC98] suggested that Bayesian networks could be utilized in the development of the iterative algorithm structure instead of some ad hoc arguments. This approach became gradually the general approach taken in this thesis.

However, the sum-product algorithm can be relatively complex for general single-connected Bayesian networks. Since the goal was to have an algorithm that has a manageable complexity the iterative receiver structure needed to be selected carefully. There are some known Bayesian network structures, where the sum-product algorithm reduces to an algorithm that has a manageable complexity. The two main cases of interest here are:

- A simple star-like structure where the sum-product algorithm reduces to likelihood calculations with closed expressions (e.g. Figure 4).
- A chain-like structure that allows the use of backward-forward algorithm (e.g. Figure 5). This kind of structure typically arises from channel coding and this algorithm is in that case the well-known APP decoder.

If the Bayesian network presenting the problem can be partitioned to components that have one of the given structures, one can approximate the sum-product algorithm by iteratively executing the simplified algorithm in the component graphs and by exchanging the probability information through the random variables common to the components. It should be emphasized that the accuracy or even the convergence of this kind of iterative approximation has not yet been proven although there is a strong body of experimental evidence to suggest that the approximation is good [MMC98].

6.1.1 Use of Bayesian networks in basic algorithm design

After the general approach was clear the first step in the actual research work was to formulate the coded multiuser detection problem. With the notation of [P1], this problem can be described in a symbol level system model as

$$\mathbf{y}_i = \mathbf{R}\mathbf{A}\mathbf{x}_i + \mathbf{n}_i , \tag{24}$$

where $\mathbf{R}$ is the cross correlation matrix, $\mathbf{A}$ is the amplitude matrix, $\mathbf{n}_i$ is the channel noise term and $\mathbf{x}_i = (x_i^{(1)}, \ldots, x_i^{(K)})^{\mathrm{T}}$ is the coded data vector containing the transmitted data symbols of every users. For every user it is an output from some encoding process that can be expressed by a state machine:

$$\begin{cases} s_j^{(k)} = g(s_{j-1}^{(k)}, u_j^{(k)}) \\ x_{Rj+l}^{(k)} = f_l(s_j^{(k)}), l = 1, \ldots, R \end{cases} \tag{25}$$

Given the random variables in the system model, one can construct the corresponding Bayesian network. The resulting full graph is too complex to be presented here in detail. In some specific cases even the full graph is simple enough to be presented. For instance the graph corresponding the case with two users and rate ½ code is shown in Figure 10. A high-level view of the general case, which is used as a basis for partitioning the graph into suitable components, is shown in Figure 15.

The general-case Bayesian network can be constructed from component graphs of two different types: type A shown in detail in Figure 16 and type B shown in Figure 17. The partitioning of the full Bayesian network into these components is also shown in Figure 15. There is one component graph of type A for every user *k* consisting of the uncoded data symbols $u_j^{(k)}$, the state variables $s_j^{(k)}$ and the transmitted data symbols $x_i^{(k)}$. There is one component graph of type B for every received symbol consisting of the received symbol $y_i^{(k)}$ together with the transmitted data symbols of all the users $x_i^{(k)}$. Note that the transmitted data symbols $x_i^{(k)}$ are included in both component graph types.

Given this partitioning into component graphs we can now approximate the sum-product algorithm by executing the algorithm in the component graphs, exchanging the probability information through the common variables $x_i^{(k)}$ in different component graphs and by reiterating the process. However, first we need to investigate what the sum-product algorithm looks like in the component graphs of type A and B.

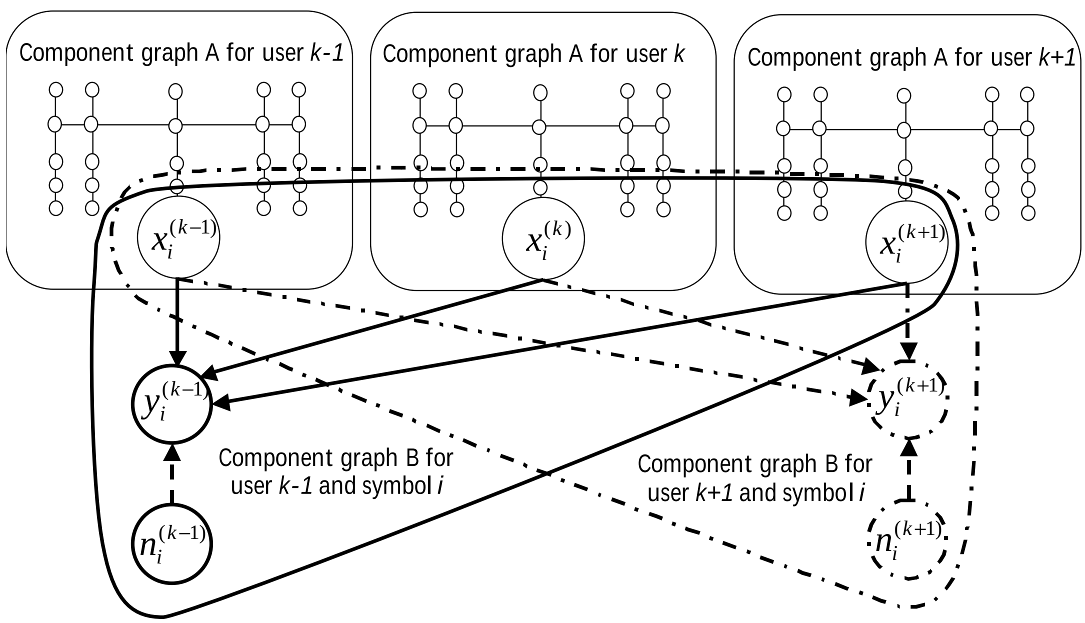

Figure 15 Graph of the general case coded MUD with partitioning

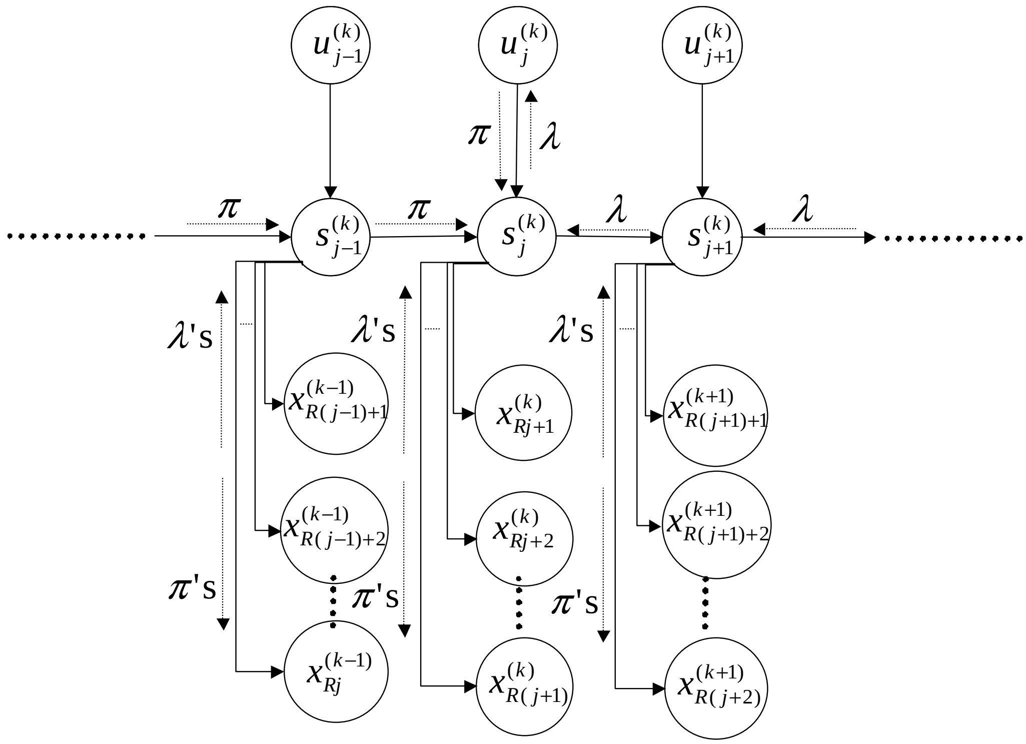

Figure 16 Component graph of Type A

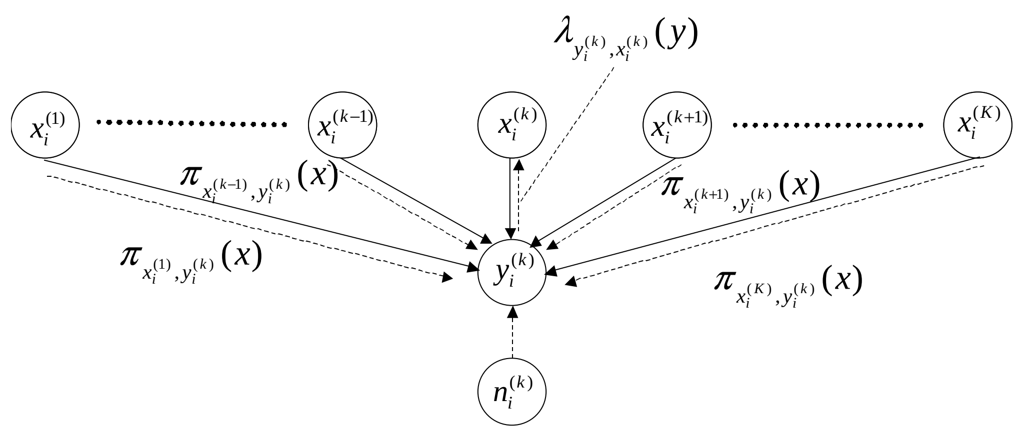

Figure 17 Component graph of Type B

Sum-product algorithm for graphs of Type A

In essence, the sum-product algorithm calculates the probabilities $p(u_i^{(k)})$ (and new estimates for $p(x_i^{(k)})$ if necessary) given the probabilities of the transmitted data symbols $p(x_i^{(k)})$ and the knowledge of the encoder state machine expressed by (25). It is based on passing two types of messages between the nodes representing the random variables, the "likelihood" messages λ and the “probability” messages π (See Figure 16). In the case of a chain-like structure of Type A, messages are first passed from the nodes representing the transmitted symbols $x_i^{(k)}$ and the user symbols $u_j^{(k)}$ to the nodes representing the state variables $s_j^{(k)}$. In the second state, a sequence of messages is passed both forward and backward in the “chain” consisting of the nodes representing the state symbols. Finally, messages are passed from state variable nodes to nodes representing the transmitted symbols $x_i^{(k)}$ and the user symbols $u_j^{(k)}$. The probabilities $p(u_i^{(k)})$ (and $p(x_i^{(k)})$ if necessary) can be calculated using the content of these messages. This is in essence the generalized forward-backward algorithm.

Next we describe the content of the messages and the calculations done in each node in more detail. In general, given some random variables *X* and *Y*, where *Y* is dependent on *X*, the message λ from *Y* to *X* contains a list of nonnegative number indexed by the value range of *X*. If *x* is a variable taking values in the range of X, then the likelihood message is often denoted by $\lambda(Y \to X)(x)$. Informally it is the probability of the “evidence” for the node representing *Y* conditioned on *X*=*x*. Similarly, the message π from *X* to *Y* contains a list of probabilities. It is indexed by the value range of *X* and denoted by $\pi(X \to Y)(x)$, where *x* is the indexing variable. Roughly, for each *x* this is the probability of the event *X*=*x* conditioned on the “evidence” in the tree “behind” the random variable that originates the message.

Looking at a Type A graph in Figure 16, the following messages are passed. The message $\lambda(x_{Rj+l}^{(k)} \to s_j^{(k)})(s)$ from node $x_{Rj+l}^{(k)}$ to node $s_j^{(k)}$ is $\lambda(x_{Rj+l}^{(k)} \to s_j^{(k)})(s) = p\left(x_{Rj+l}^{(k)} = f_l(s)\right)$ for all possible values of *s*. This can be calculated from the probability distributions $p(x_{Rj+l}^{(k)})$ originating from component graph B, since f_l is known.

Similarly, the message $\pi(u_j^{(k)} \to s_j^{(k)})(u)$ from $u_j^{(k)}$ to $s_j^{(k)}$ is the probability of the event $u_j^{(k)} = u$ conditioned on the “evidence” in the tree “behind” $u_j^{(k)}$. This is in fact just the *a priori* probability. Thus we have $\pi(u_j^{(k)} \to s_j^{(k)})(u) = p(u_j^{(k)} = u)$.

Moving to the more complicated cases, the message $\lambda(s_{j+1}^{(k)} \to s_j^{(k)})(s)$ from $s_{j+1}^{(k)}$ to $s_j^{(k)}$ is the marginalized probability

$$\lambda(s_{j+1}^{(k)} \to s_j^{(k)})(s) = \sum_u p(u_{j+1}^{(k)} = u)\lambda(s_{j+2}^{(k)} \to s_{j+1}^{(k)})\big(g(s,u)\big)\prod_l p(x_{R(j+1)+l}^{(k)} = f_l(g(s,u)) \qquad (26)$$

$$= \sum_u \pi(u_{j+1}^{(k)} \to s_{j+1}^{(k)})(u)\lambda(s_{j+2}^{(k)} \to s_{j+1}^{(k)})\big(g(s,u)\big)\prod_l \lambda(x_{R(j+1)+l}^{(k)} \to s_{j+1}^{(k)})(f_l(g(s,u)))$$

for all possible values of *s*. Thus this is effectively calculated from $p(x_{j+1}^{(k)}), \ldots, p(x_N^{(k)})$ and the *a priori* probabilities $p(u_{j+1}^{(k)}), \ldots, p(u_N^{(k)})$ in a recursive manner.

Correspondingly, a message $\pi(s_{j-1}^{(k)} \to s_j^{(k)})(s)$ passed from $s_{j-1}^{(k)}$ to $s_j^{(k)}$. Again, for each *s* this is the probability of the event $s_{j-1}^{(k)} = s$ conditioned on the "evidence" in the tree "behind" $s_{j-1}^{(k)}$. Thus we obtain

$$\pi(s_{j-1}^{(k)} \to s_j^{(k)})(s) = \sum_{s',u:g(s',u)=s} p(u_{j-1}^{(k)} = u)\, p(s_{j-2}^{(k)} = s')\prod_l p(x_{R(j-1)+l}^{(k)} = f_l(s)) \qquad (27)$$

$$= \sum_{s',u:g(s',u)=s} \pi(u_{j-1}^{(k)} \to s_{j-1}^{(k)})(u)\lambda(s_{j-2}^{(k)} \to s_{j-1}^{(k)})(s')\prod_l \lambda(x_{Rj+l}^{(k)} \to s_{j-1}^{(k)})(f_l(s))$$

for all possible values of *s*. Thus this is effectively calculated from $p(x_1^{(k)}), \ldots, p(x_{j-1}^{(k)})$ and the *a priori* probabilities $p(u_1^{(k)}), \ldots, p(u_{j-1}^{(k)})$ in a recursive manner.

After both the forward and the backward message passing phases have completed, the likelihood message $\lambda(s_j^{(k)} \to u_j^{(k)})(u)$ can be transmitted from $s_j^{(k)}$ to $u_j^{(k)}$. This can be calculated as

$$\lambda(s_j^{(k)} \to u_j^{(k)})(u) = \sum_s \pi(s_{j-1}^{(k)} \to s_j^{(k)})(s)\lambda(s_{j+1}^{(k)} \to s_j^{(k)})(g(s,u))\prod_l \lambda(x_{R(j+1)+l}^{(k)} \to s_j^{(k)})(f_l(g(u,s))) \qquad (28)$$

The symbol probabilities can now be calculated as $p(u_i^{(k)}) = \lambda(s_j^{(k)} \to u_j^{(k)})(u_i^{(k)})$.

In iterative receiver we also need to update the probabilities $p(x_i^{(k)})$. These are updated based on the message $\pi(s_j^{(k)} \to x_{R(j+1)+l}^{(k)})(s)$ transmitted from $s_j^{(k)}$ to $x_{R(j+1)+l}^{(k)}$. The content of this message is

$$\pi(s_j^{(k)} \to x_{(Rj+1)+l}^{(k)})(s) = \sum_{s',u:g(s',u)=s} \pi(u_j^{(k)} \to s_j^{(k)})(u)\pi(s_{j-1}^{(k)} \to s_j^{(k)})(s')\lambda(s_{j+1}^{(k)} \to s_j^{(k)})(s)\prod_{l'\neq l} \lambda(x_{R(j+1)+l'}^{(k)} \to s_j^{(k)})(f_{l'}(s)) \tag{29}$$

The symbol probabilities can be calculated as

$$p(x_{R(j+1)+l}^{(k)}) = \sum_{s:f_l(s)=x_{R(j+1)+l}^{(k)}} \pi(s_j^{(k)} \to x_{(Rj+1)+l}^{(k)})(s)\,. \tag{30}$$

The formulas above are in fact equivalent to the calculations done in *a posteriori* probability (APP) decoding algorithm also called maximum *a posteriori* (MAP) decoding algorithm. Furthermore, in this case the sum-product algorithm with the given message passing scheduling is actually functionally equivalent to APP decoding algorithm [MMC98]. Thus the calculation can in practice be done by using the APP decoding algorithm.

Sum-product algorithm for graphs of Type B

In the component graph of Type B the sum-product algorithm effectively calculates the probability $p(y_i \mid x_i^{(k)})$. Following the steps in the sum-product algorithm, then messages

$$\pi(x_i^{(h)} \to y_i^{(k)})(x) = p(x_i^{(h)} = x) \tag{31}$$

are first transmitted to the node $y_i^{(k)}$ for all $h \neq k$. The message transmitted to node $x_i^{(k)}$ is

$$\begin{aligned}\lambda(y_i^{(k)} \to x_i^{(k)})(x) &= \sum_{\mathbf{x}_i:x_i^{(k)}=x} p(y_i^{(k)} \mid \mathbf{x}_i)\prod_{h\neq k} \pi(x_i^{(k)} \to y_i^{(k)})(x_i^{(h)}) \\ &= \sum_{\mathbf{x}_i:x_i^{(k)}=x} p(y_i^{(k)} \mid \mathbf{x}_i)\prod_{h\neq k} p(x_i^{(h)})\,.\end{aligned} \tag{32}$$

If the observed value for $y_i^{(k)}$ is y_0, then the message transmitted to node $x_i^{(k)}$ is thus

$$\lambda(y_i^{(k)} \to x_i^{(k)})(x) = p(y_i = y_0 \mid x_i^{(k)} = x)\,. \tag{33}$$

Note that Equation (12) in [P1] is essentially just the Equation (32) for log-likelihood ratios. The new value for the probability $p(x_i^{(k)})$ that is passed to component graphs of Type A can be calculated recursively as

$$p(x_i^{(k)}) = p(y_i = y_0 \mid x_i^{(k)})\, p(x_i^{(k)}) = \lambda(y_i^{(k)} \to x_i^{(k)})(x)\, p(x_i^{(k)})\,. \qquad (34)$$

Basic Iterative Algorithm used in [P1]-[P3]

Now we can combine the two algorithms to obtain the basic iterative algorithm used in [P1]-[P3]. The random variables $x_i^{(k)}$ are the common variables both component graph types and we obtain an approximate algorithm for calculating $p(u_i^{(k)} \mid y_i^{(k)})$ as follows:

1. Set the probabilities $p(x_i^{(k)})$ to some initial value, e.g. ½.
2. From the observed values for y_i calculate the $p(y_i^{(k)} \mid x_i^{(k)})$ in component graphs of type B. In practice Equation (32) is used. In the publications [P1]-[P3] also suboptimal variants of this calculation are used. See Section 6.1.2 for more discussion on these.
3. Update $p(x_i^{(k)})$ by Equation (34) and pass this to the component graphs of type A. Calculate $p(u_i^{(k)})$ and $p(x_i^{(k)})$ with APP decoding algorithm.
4. Go to step 2 and use the new estimate for $p(x_i^{(k)})$. Iterate this as long as necessary.

Thus we have obtained a moderate complexity iterative algorithm Looking at the reference CDMA receiver structure in Figure 3, the soft information is passed a reference points A and D. In reference point E soft or hard information can be used, although in the simulations hard decisions were made at this point an the resulting bit error rate (BER) was calculated. In this study, convolutional coding was assumed and thus there were no constituent decoders or reference points B and C. However, it is straightforward to extend this work to systems using Turbo codes.

In this section we have described how Bayesian networks was utilized to develop and understand the iterative coded multiuser receiver studied in publications [P1]-[P3]. In the next section we summarize the research work done for this topic.

6.1.2 Summary of the research performed on coded multiuser detection

The starting point of the research reported in publications [P1]-[P3] was the iterative algorithm discussed in Section 6.1.1. Several further developments took place during the research activity. These are summarized in this section.

As was mentioned in Section 6.1.1 the sum-product algorithm for Bayesian network in Figure 16 is functionally equivalent the well-known APP (also known as MAP) algorithm [MCC98]. Thus the basic iterative receiver structure can be described using the APP decoder and likelihood calculation formula without explicitly mentioning Bayesian networks. This approach was taken first in [P1] and later as a general approach in this study. The main rationale behind this decision was that using commonly known techniques in the publications made those both simpler and easier to understand for an average reader. One major factor impacting this decision was the lack of any theoretical results regarding the convergence of iterative approximation for sum-product algorithm.

The graph in Figure 17 is so simple that the sum-product algorithm results a closed-from expression. Nevertheless, the calculation of summation in Equation (32) is still relatively complex to be implemented in a base station receiver. Thus in [P1] two suboptimal alternatives were proposed. The hard decision likelihood calculation was derived by approximation the logarithm of the sum by the maximum of the logarithms; a common method used in both Turbo decoding and Bayesian networks [BDM96]. In essence, the following approximation is used.

$$\begin{aligned}\log \lambda(y_i^{(k)} \to x_i^{(k)})(x) &= \log\left(\sum_{\mathbf{x}_i : x_i^{(k)} = x} p(y_i^{(k)} \mid \mathbf{x}_i) \prod_{h \neq k} p(x_i^{(h)})\right) \\ &\approx \max_{\mathbf{x}_i : x_i^{(k)} = x}\left(\log\, p(y_i^{(k)} \mid \mathbf{x}_i) + \sum_{h \neq k} \log p(x_i^{(h)})\right).\end{aligned} \tag{35}$$

Assuming that we have a very reliable estimate $\hat{\mathbf{x}}_i$ and thus $P(\hat{\mathbf{x}}_i) \approx 1$, then the max-log approximation in (35) results

$$\log \lambda(y_i^{(k)} \to x_i^{(k)})(x) \approx \begin{cases} \log\, p(y_i^{(k)} \mid \hat{\mathbf{x}}_i), & \text{if } \hat{x}_i^{(k)} = x \\ -\infty, & \text{otherwise} \end{cases} \tag{36}$$

When this approximation is used $\log\, p(y_i^{(k)} \mid \hat{\mathbf{x}}_i)$ is calculated as follows:

$$\log\, p(y_i^{(k)} \mid \hat{\mathbf{x}}_i) = \frac{1}{2\sigma^2}\left(y_i^{(k)} - \left(\mathbf{R}\mathbf{A}\hat{\mathbf{x}}_i\right)^{(k)}\right) + \text{constant}. \tag{37}$$

Thus this approximation is in fact hard decision interference cancellation followed by likelihood calculation for an AWGN channel with variance σ^2.

The second alternative is otherwise the same as the previous one, but it uses the expectation value of the transmitted channel symbol instead of the hard decision value in the likelihood calculation. In the binary case using log-likelihood ratios, this is just a hyperbolic tangent of a scaled log-likelihood ratio for the transmitted channel symbol.

For all these likelihood calculation methods an estimate of channel variance is needed for the calculation of the distribution of $y_i^{(k)}$, which is the only continuous random variable in the Bayesian network describing the system model. Theoretically, an estimate of the variance σ^2 should be used. During the simulations done for [P1] and [P2] it became evident that the convergence speed of the suboptimal alternatives can be substantially increased if a larger value is used for this estimate during the first simulation steps. This kind of behavior is typical to approximate iterative methods and the only difficulty is usually to determine the correct rate of decreasing the value. Since both suboptimal algorithms can be expressed by an interference cancellation step followed by a likelihood calculation step, it was natural to use the variance of the modified samples after each interference cancellation. The simulations showed that with this modification, even the hard decision interference cancellation performance was close to optimal likelihood calculation performance. This was one of the key findings reported in [P1].

In [P1], a simple averaging was used to obtain the variance estimate. Naturally some more advanced estimation methods could increase the performance gain. Since the variance re-estimation had a significant impact on the performance of the suboptimal algorithms, this was investigated further in [P2]. It was found that the use of improved variance estimation method taken from [RA97] slightly improved the convergence of the hard decision IC algorithm.

In addition to the increased complexity, the main difficulty in using iterative joint multiuser receivers - or IC receivers with decoded tentative decisions - in fading channels is the prohibitively long delay caused by the interleaved channel codes. Currently interleaving is virtually always used in channel codes designed for fading channels, because it is a relatively simple method to obtain the required time diversity. However, in order to obtain this time diversity, the interleaving block length must be substantially longer than the channel coherence time. On the other hand, the whole interleaving block must be received before the iterative detection/decoding process can take place. This means that there is a significant delay between the actual reception of the signal and the actual availability of the receiver symbol. This is unacceptable for delay-sensitive applications, but it is really catastrophic for fast power control, which is used in wideband CDMA systems. The operation of the fast power control requires the transmission power to be adjusted based on the received power control (PC) bit. This needs to be done with a reasonably low delay and the delay induced by the iterative joint detection/decoding is just unacceptable high.

One way to reduce the delay is to utilize a coding scheme, which is a concatenation of an inner non-interleaved code and an outer interleaved code for coded multiuser detection. In this approach only the inner code would be used in the multiuser detection and the delay between the symbol reception and the availability of the detected symbols would be reduced. This observation motivated the work reported in [P3], where we estimated the capacity of such CDMA receivers when operating over a correlated Rayleigh fading channel. The analysis shows that interleaving is not necessary for good *interference cancellation* performance even in correlated fading channels. In fact, in a correlated Rayleigh fading channel, the performance of an IC receiver using decoded tentative decisions and a relatively weak non-interleaved code will be near the single-user performance limit.

Even with this approach, there are significant system level problems for current WCDMA system (UTRAN FDD mode) specified by 3GPP, where the channel decoding is done for blocks that have duration a multiple of 10ms, but the power control command is sent for each slot, that is, once for every 666 μs [3GPPc]. Thus from system perspective even this approach is not feasible unless significant changes are made for layer 1 structure in UTRAN FDD mode. At the moment this does not seem feasible.

One remaining possibility is to apply the coded multiuser detection only for WCDMA data channel, not for the control channel where the power control bits are transmitted. This approach is not studied further in this thesis.

6.2 SOFT-OUTPUT RAKE RECEIVERS FOR CDMA MOBILE TERMINALS

In papers [P4], [P5] and [P6] we study the performance improvement achieved by using soft decision and decoding techniques in CDMA downlink. As for the base station receivers, the detection and decoding problem for mobile receiver can also be regarded as a problem of probabilistic inference in a Bayesian network. In the downlink the channelisation codes for different users are orthogonal, but with multipath propagation, the signals traveling via different paths are misaligned in time and *interpath interference* is introduced even when orthogonal codes are used for different users. Thus there is interference both between different users as well as between different symbols. In this case however, the limited processing power of a mobile terminal does not allow the use of iterative methods considered for coded multiuser detection in Section 4, especially given the lower achievable gain implied by the interference levels that are much smaller than for uplink MAI.

Based on the above considerations a different starting point was selected for this part of research and the interfering users were modeled as Gaussian noise in the Bayesian network. The aim was to derive receivers that take into account channel estimation errors, do not require variance estimation and that also are suitable for higher modulation schemes.

6.2.1 Use of Bayesian networks in basic algorithm design

The symbol level system model from [P5] is

$$y_l(n) = h_l(n)x(n) + w_l(n)\,, \tag{38}$$

where $h_l(n)$ are the channel coefficients, $w_l(n)$ is the combined channel noise and interference with variance σ_l^2, and *x(n)* is the coded channel symbol obtained from

$$\begin{cases} s_j = g(s_j, u_j) \\ x(Rj + l) = f_l(s_j), l = 1, \ldots, R \end{cases} \tag{39}$$

The resulting Bayesian network is shown in Figure 18. Note that this graph is not multiply-connected and thus the sum-product results the exact probabilities. Nevertheless, partitioning the graph into simpler components is still useful to identify the appropriate receiver structure.

In the same way as for the uplink coded multiuser detection, this graph can be partitioned into the chain-like component of Type A arising from channel coding shown in Figure 19 and the likelihood calculation component shown in Figure 20.

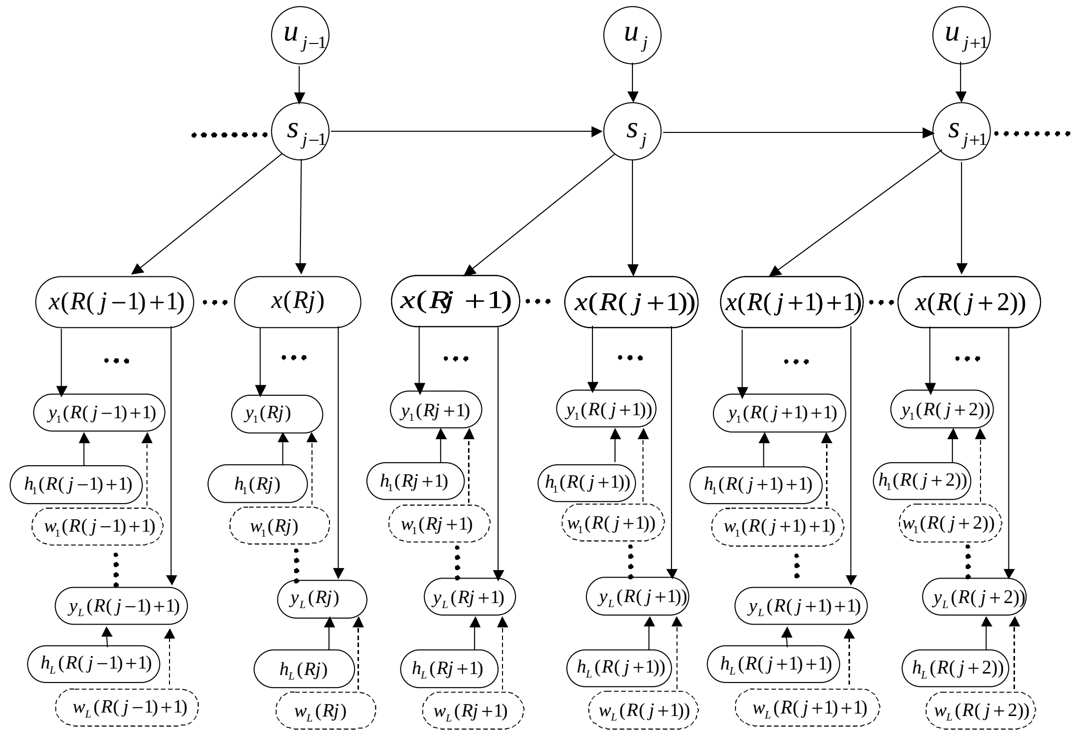

Figure 18 Bayesian network presenting the downlink system model

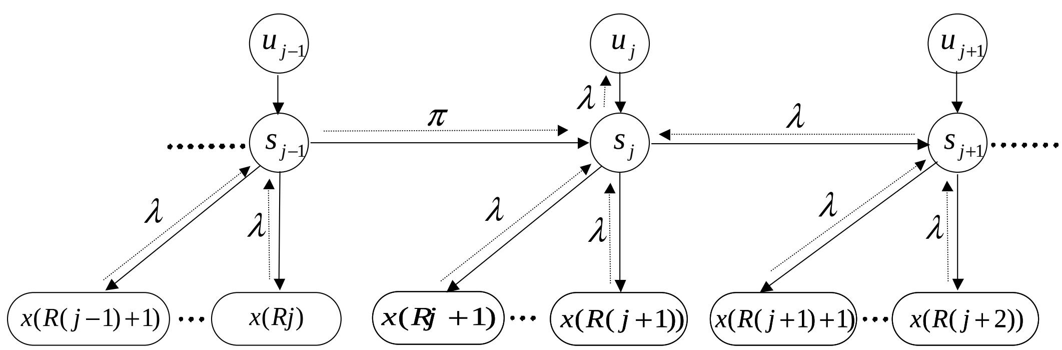

Figure 19 Chain-like component of Type A in downlink model

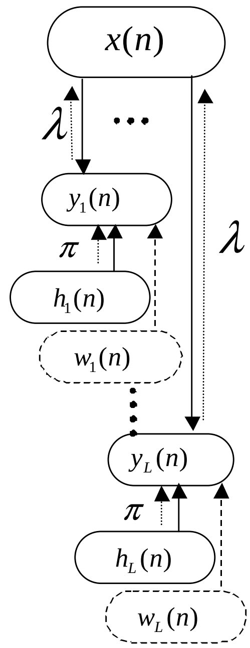

Figure 20 Likelihood calculation component graph in downlink model

Since the component graph in Figure 19 is of Type A, the APP decoding can again be used to calculate the probabilities. However, the message passing between the components is in this case only one-way and thus the resulting receiver structure is non-iterative. Looking at the reference CDMA receiver structure, this corresponds to a case where no information is passed at reference point D and soft information is passed at reference point A and hard information in reference point E. Again there are no constituent decoders and thus reference points B and C do not exist. As a result the channel decoder does not need to provide soft output. Thus any soft decision decoding algorithm is applicable. In publications [P4]-[P6] the Viterbi algorithm was used in the simulations to achieve low complexity.

For the component graph shown in Figure 20 the most significant feature is that there is message passing between $h_l(n)$'s and the corresponding $y_l(n)$'s, which are both continuous-valued random variables. This creates some difficulties since the corresponding message $\pi(h_l(n) \to y_l(n))(h)$ lists a non-negative real value for every possible value of the random variable. The problem is how to handle these infinite lists in the practical implementation of the algorithm. Furthermore, the summations in the sum-product algorithm become integrations for continuous-valued random variables, which complicates the situation even more. This can be seen in message $\lambda(y_l(n) \to x(n))(x)$, which can be expressed as

$$\lambda(y_l(n) \to x(n))(x) = \int \pi(h_l(n) \to x(n))(h)\, p(y_l(n) \mid h_l(n) = h, x(n) = x)\; dh\,. \qquad (40)$$

Finally, we also need to take into account the channel estimates $\hat{h}_l(n)$ available in the receiver when calculating the likelihoods. Two alternative approaches for doing this were used in this study.

In [P4] and [P6] we pass a list containing only one entry $\pi(h_l \to y_l) = \{\hat{h}_l(n)\}$. With only this information available, the random variable $h_l(n)$ is effectively treated as an observed variable. We obtain

$$\begin{aligned}\lambda(y_l(n) \to x(n))(x) &= p(y_l(n) \mid h_l(n) = \hat{h}_l(n), x(n) = x) \\ &= \frac{1}{\pi\sigma_l^2}\exp\left(-\frac{1}{\sigma_l^2}\left|y_l(n) - \hat{h}_l(n)x\right|^2\right)\end{aligned} \qquad (41)$$

In the Viterbi decoder implementing the algorithm for component graph in Figure 19, these likelihood messages are used to calculate the conditional probabilities $p(\mathbf{y}(n) \mid x(n)) = \prod_l \lambda(y_l(n) \to x(n))(x(n))$ required in Viterbi decoding. As a result we obtain that the input for the Viterbi decoder is

$$p(\mathbf{y}(n) \mid x(n)) = \prod_l \frac{1}{\pi\sigma_l^2}\exp\left(-\frac{1}{\sigma_l^2}\left|y_l(n) - \hat{h}_l(n)x(n)\right|^2\right). \qquad (42)$$

This formula is a special case of Equation (16) in [P5], when $\sigma_{z_l}^2 = 0$. Following the same reasoning as in Section 3.3 in [P5] and defining F as an arbitrary positive real constant, we can conclude that for constant-amplitude modulation schemes this probability can be expressed as a transformation of metric

$$\Lambda(\mathbf{y}(n) \mid x(n)) = \mathrm{Re}\left\{\sum_l \frac{F\hat{h}_l(n)^*}{\sigma_l^2} y_l(n)x(n)^*\right\}, \qquad (43)$$

which is obtaining through the use of conventional RAKE receiver with Brennan’s MRC scheme. In practice this means that for constant-amplitude modulation schemes the metric (43) can be used as the input for the Viterbi decoder. Using this connection between the probabilities and the MRC one can derive new enhanced MRC schemes using the results obtained by considering Bayesian networks. This was the approach taken for [P4] and [P6].

When this method is used, any channel estimation error is propagated to the likelihood calculation in node representing $y_l(n)$. In [P6] we used the assumption that the channel estimates are perfect for the analysis and simulations. In the scheme proposed in [P4], these estimation errors are taken into account in the likelihood calculation by treating the channel estimation error in the same way as the noise-and-interference terms $w_l(n)$'s. This can be done when a constant-amplitude modulation scheme is used.

In [P5] we take a different approach and pass the observed mean value $\hat{h}_l(n)$ of the channel coefficient together with an estimate of the variance to the node representing $y_l(n)$'s. This means that the message is $\pi(h_l(n) \to y_l(n)) = \{\hat{h}_l(n), \sigma_{z_l}^2\}$. For brevity of the notation we define in the following $\pi = \pi(h_l(n) \to y_l(n))$. The channel coefficients $h_l(n)$ are assumed to be complex Gaussian random variables, and either by directly integrating (40) or by using the same reasoning as in [P5] we obtain:

$$\begin{aligned}&\lambda(y_l(n) \to x(n))(x) = \\ &\frac{1}{\pi}\frac{1}{|x|^2\ \pi(2) + \sigma_l^2} \exp\left(-\frac{1}{|x|^2\ \pi(2) + \sigma_l^2}\left|y_l(n) - \pi(1)x\right|^2\right).\end{aligned} \tag{44}$$

As before, in the Viterbi decoder implementing the algorithm for component graph in Figure 19, these likelihood messages are used to calculate the conditional probabilities required in Viterbi decoding as

$$\begin{aligned}p(\mathbf{y}_l \mid x(n)) &= \prod_l \lambda(y_l(n) \to x(n))(x(n)) \\ &= \prod_l \frac{1}{\pi}\frac{1}{|x(n)|^2\ \pi(2) + \sigma_l^2} \exp\left(-\frac{1}{|x(n)|^2\ \pi(2) + \sigma_l^2}\left|y_l(n) - \pi(1)x(n)\right|^2\right) \\ &= \prod_l \frac{1}{\pi}\frac{1}{|x(n)|^2\ \sigma_{z_l}^2 + \sigma_l^2} \exp\left(-\frac{1}{|x(n)|^2\ \sigma_{z_l}^2 + \sigma_l^2}\left|y_l(n) - \hat{h}_l(n)x(n)\right|^2\right)\end{aligned} \tag{45}$$

This is the Equation (16) in [P5] presenting the correct input to the Viterbi decoder. In that publication an estimate of variance $\sigma_{z_l}^2$ is obtained by weighting an analytical noise-and-interference power estimate with a estimator diversity factor. This scheme is applicable to all modulation schemes.

6.2.2 Summary of the research performed on soft-output RAKE receivers

The starting point for this research was the considerations discussed in Section 6.2.1. Again, the approach was not to use Bayesian network approach explicitly in the publications in order to simplify the derivations. However, these considerations played a major role when developing the initial algorithms.

In [P4] we proposed a modified maximal ratio combining (MRC) scheme that is more suitable for RAKE receivers in wideband code division multiple access (WCDMA) mobile terminals then the conventional MRC scheme. In this case Equation (43) was used. The channel estimation errors were taken into account in the likelihood calculation where the channel estimation error was treated in the same way as the noise-and-interference terms $w_l(n)$'s. This approach is possible when a modulation scheme is used that has constant amplitude constellation points. For simplicity of the presentation, the results in [P4] were presented based on Brennan's MRC scheme. In particular, a modified MRC scheme corresponding the results shown in Section 6.2.1 was derived analytically assuming unequal noise powers and imperfect channel estimates in different RAKE fingers.

In [P5] we proposed an improved soft-output RAKE detector providing a more accurate metric in these situations and thus giving a performance gain especially with low spreading gains and high-order modulation schemes. The proposed receiver produces a bit metric for the soft-decision decoder taking into account the multipath fading channel, the interfering users and the channel estimation errors. For this publication Equation (45) was utilized. For simplicity, the results in the publication were derived without explicitly using Bayesian networks. We first formulated the system model containing the transmitter, channel and RAKE correlator finger models. Then we derived the optimum symbol metric based on the system models, assuming that the interference and channel noise are Gaussian distributed and uncorrelated both in time and between the RAKE fingers. The channel estimation errors were assumed to be Gaussian distributed. The optimum metric calculation requires the estimation of the noise variance in different RAKE finger outputs. To make our proposed soft-output RAKE receiver feasible in practice, we used a metric that employs an analytical estimate of the noise variances without requiring explicit noise variance estimation. Finally, we presented simulation results showing that a clear performance gain when low spreading factors or high-order constellations were used.

In [P6] we proposed an improved maximal ratio combining (MRC) scheme for RAKE receivers in Mobile CDMA terminals. It was based on the original MRC scheme derived by Brennan and performed nearly as well as Brennan's method. However, unlike Brennan's method, our improved scheme did not require the estimation of the RAKE finger noise powers. We also analyzed the gain obtained through the use of Brennan's MRC scheme for mobile CDMA terminals, and showed that both the Brennan's original MRC scheme and, more importantly, our improved scheme results in significantly higher signal-to-noise ratios than the conventionally used MRC scheme. Simulations were also presented to further compare the performance of the conventional MRC and our proposed MRC scheme.

6.3 ORIGINALITY AND CONTRIBUTION OF THE PUBLICATIONS

In this section we list these contributions in detail for each publication and summarize the major and minor achievements in the publications constituting this thesis.

In [P1] an iterative receiver structure that utilizes the decoding information for multiuser detection was proposed and analyzed. The receiver structure was suggested by the ideas described in Section 6.1.1. The optimal as well as two suboptimal multiuser likelihood calculation algorithms were presented. Similar approaches had been independently studied in [REA97] and [HSH97]. In [REA97] a different likelihood calculation method was proposed than in [P1]. In [HSH97], which was not known to the author at the time of this research, an IS-95 system was studied and the optimum likelihood calculation similar to the one presented in [P1] was derived along with some suboptimal alternatives. The method for derivation and the suboptimal alternatives were different from those given in [P1]. Furthermore, the impact of variance estimation was not discussed in [HSH97]. Thus the major novel contributions in [P1] were the proposed suboptimal likelihood calculation algorithms utilizing the variance re-estimation approach, which significantly improved the performance of the suboptimal algorithms. This approach was discovered through the Bayesian network considerations discussed in Section 6.1. These contributions were novel and previously unpublished.

Since the variance estimation was found to have a significant impact on the suboptimal algorithms in [P2] the impact of different variance estimators was studied. The main contribution in this publication was to show how the more advanced channel variance estimation method presented in [RA97] could be used to improve the suboptimal hard decision algorithm proposed in [P1]. This contribution was novel and not previously reported anywhere.

The work reported in [P3] was motivated by the discovery of the system issues discussed in Section 6.1. The iterative coded multiuser detection with interleaved channel coding causes delays that are problematic especially for fast power control. To evaluate the feasibility of having a non-interleaved simple inner code that would be used in coded multiuser detection, it was necessary to analyze the interference cancellation performance in correlated Rayleigh channel when such code is used. This was done in [P3].

There were two novel contributions in this publication. First, we derived an iterative way of analytically estimating the amount of noise present at *m*th stage in an interference cancellation (IC) receiver utilizing channel coding. Furthermore, by calculating the error probabilities for non-interleaved codes in correlated Rayleigh channel, we were able to analytically estimate the performance of IC CDMA receivers that are using non-interleaved channel coding to improve the reliability of the tentative decisions. Second, we estimated the performance of such receivers in correlated Rayleigh channels through simulations. Both results were novel and not reported before.

At this point the focus of the research was shifted due to some external circumstances. Thus in [P4], [P5] and [P6] we studied the performance improvement achieved by using soft decision and decoding techniques in CDMA downlink. In this case non-iterative receivers were considered.

In [P4] a modified maximal ratio combining (MRC) scheme was proposed that was based on the ideas described in Section 6.2.1. This scheme is more suitable for RAKE receivers in wideband code division multiple access (WCDMA) mobile terminals than the conventional MRC scheme. The main contribution in this paper was a novel MRC scheme, which takes into account the different noise powers in different fingers in a similar way as the suboptimal scheme proposed in [TSW00], but also takes into account the channel estimation errors.

In [P5] we proposed an improved soft-output RAKE detector that provides a more accurate metric and gives a performance gain especially with low spreading gains and high-order modulation schemes. It was based on the considerations described in Section 6.2.1 and used a bit metric for the soft-decision decoder taking into account the multipath fading channel, the interfering users and the channel estimation errors. The major novel contributions in this publication were the new bit metric for the soft-decision decoder, which is suitable also for higher-order modulation schemes, the method to estimate the noise powers in different fingers based on the channel estimates and an analytical method to estimate channel estimation errors. These results were novel and previously unpublished.

In [P6] we proposed an improved maximal ratio combining (MRC) scheme for RAKE receivers in mobile CDMA terminals. The algorithm was similar to the one presented in [TSW00] and [P4]. However, here the analytical estimate of the noise powers developed in [P5] were used. We also analyzed the gain obtained through the use of Brennan's MRC scheme for mobile CDMA terminals, and showed that both the Brennan's original MRC scheme and, more importantly, our improved scheme results in significantly higher signal-to-noise ratios than the conventionally used MRC scheme. The major contributions in this paper were the use of the analytical estimate of the noise powers needed for the enhanced MRC and the analysis of the MRC schemes. These results were novel and not reported before.

The major achievements in this thesis are the following:

- In [P1], the suboptimal multiuser likelihood algorithms utilizing the variance re-estimation approach, which significantly improves the performance of these suboptimal algorithms.
- In [P3], the derivation of an iterative way to analytically estimate the amount of noise present at *m*th stage in a coded interference cancellation (IC) receiver and the analytical estimate of the correlated channel performance of IC CDMA receivers that are using non-interleaved channel coding to improve the reliability of the tentative decisions.
- In [P5], a new bit metric for the soft-decision decoder, which is suitable also for higher-order modulation schemes, the method to estimate the noise powers in different fingers based on the channel estimates and the analytical method to estimate channel estimation errors.
- In [P6] the analysis of the performance of different MRC schemes.

The minor achievements in the thesis are the following:

- The work in [P2] showing how the more advanced channel variance estimation methods presented can be used to improve the suboptimal hard decision algorithm.
- In [P3] the performance simulations of the coded interference cancellation receivers in correlated Rayleigh fading channels.
- In [P4] the enhanced MRC scheme, which takes into account the different noise powers in different RAKE fingers and the channel estimation errors.
- In [P6] the use of the analytical estimate of the noise powers in different RAKE fingers in the enhanced MRC scheme.

6.4 AUTHOR'S CONTRIBUTION TO THE PUBLICATIONS

The author's contribution has been essential to publications [P1]-[P6].

In publication [P1], the author has been responsible for development of the proposed algorithm as well as for the writing of the publication. Furthermore all simulations were carried out by the author. The second author provided valuable comments on the work and suggested several modifications substantially improving the publication.

In publications [P2]-[P4] and [P6], the author was the sole contributor.

In publication [P5], the author was responsible for development of the proposed algorithm although the development was significantly influenced by the discussions with the second author. The author carried out all simulations as well as the writing of the publication. The second author provided valuable comments on the work and suggested major modifications in the publication structure that substantially improved its quality.

7 CONCLUSIONS

The provision of high-speed, high-quality wireless data services creates a need for further development of existing receiver algorithms as well as for the creation of completely new solutions. The main problem addressed in this thesis was the application of soft detection and decoding algorithms in the receivers of the base stations as well as in the mobile terminals in a way that good performance is achieved but that the computational complexity remains acceptable.

Two specific cases were considered in this thesis: coded multiuser detection in the CDMA base station and improved RAKE-based reception employing soft detection in the mobile terminal. To review the required background, a general introduction was given in Chapter 1 followed by a short background on wireless systems and receivers in Chapter 2. In Chapter 3, soft detection and decoding was introduced starting from detection theory and introducing soft detection by considering reduced complexity methods and in particular such iterative methods where soft detection and decoding play a key role. This chapter was concluded by a review of soft detection and decoding in wideband CDMA systems.

Throughout Chapter 3, the Bayesian networks were used to illustrate the problems addressed by soft detection and decoding. This view was selected because it was the original concept of this research, but also to emphasize the underlying connection between the two apparently separate research cases considered in this thesis.

In Chapter 4, the application of soft detection and decoding was studied for coded multiuser detection in CDMA base stations. The state-of-the-art research on coded multiuser receivers was reviewed with the emphasis on iterative joint multiuser receivers, the type of receivers considered in publications [P1] and [P2]. Finally, some system issues of iterative joint multiuser receivers were considered related the analysis presented in [P3].

In Chapter 5 the application of soft detection for an improved RAKE-based reception in the mobile terminal was studied. The approach used to derive the improved RAKE receivers proposed in [P4], [P5] and [P6] was presented.

In Chapter 6, a summary of the publications and the author's contribution in those were presented. We also summarized the research work done. Since Bayesian networks were not explicitly utilized in the publications, we described how they were used in the development of the algorithms presented in the publications. The general approach was to develop the initial idea for the receiver structure using Bayesian networks, after which the detailed derivations of the various components in the receivers, such as the likelihood calculation algorithms, were done with other methods. Finally we listed the major and minor achievements in the publications constituting the thesis.

The new contributions of this thesis were made in two areas. The first part of the research focused on coded multiuser detection in the CDMA base station. The publications [P1], [P2] and [P3] contain the results of the research work related to the coded multiuser detection. The key achievements of this part of the research were development of the suboptimal multiuser likelihood algorithms in [P1] utilizing the variance re-estimation approach, which significantly improved the performance of these suboptimal algorithms as well as the work in [P2] showing how the more advanced channel variance estimation methods can be used to improve the suboptimal hard decision algorithm. In [P3], the key results were the derivation of an iterative way to analytically estimate the amount of noise present at mth stage in a coded interference cancellation (IC) receiver and the analytical estimate of the correlated channel performance of IC CDMA receivers that are using non-interleaved channel coding to improve the reliability of the tentative decisions.

The second part of the research focused on the reception in the mobile terminal and considered improved RAKE-based reception in the mobile terminal employing soft detection. The publications [P4], [P5] and [P6] contain the results of that research. The key achievements of this part of the research were the enhanced MRC scheme in [P4], which took into account the different noise powers and the channel estimation errors in different RAKE fingers. In [P5] a new bit metric was proposed for the soft-decision decoder, which was also suitable for higher-order modulation schemes. The contributions in [P5] also included a method to estimate the noise powers in different fingers based on the channel estimates and an analytical method to estimate channel estimation errors. Finally, in [P6] the key contributions were the analysis of the performance of different MRC schemes as well as the enhanced MRC scheme using the analytical estimate of the noise powers in different RAKE fingers.

8 FUTURE WORK

There are several potential ways to continue this research both in the area of coded multiuser detection as well as in the area of soft detection/decoding in mobile terminals. Moreover, at a more general level the use of Bayesian networks in the area of communications could also be investigated further. In this section we give some possible directions for future research in all of these areas.

In the area of coded multiuser detection, there is a vast body of existing research on the different receiver algorithms and on the performance gains achieved as was discussed in Section 4. However, there are several open system-level issues such as the ones discussed in Section 4.3.4. Thus the successful deployment of coded multiuser receivers in existing wideband CDMA systems requires that the feasibility of the deployment and the achievable performance gains are evaluated from the system point of view. Even with the existing knowledge it seems likely that coded multiuser detection is not very practical in systems utilizing fast power control or any other mechanisms that require low-latency feedback. One notable exception might be systems utilizing some short inner coding e.g. some short space-time block code like the Alamouti-type codes [Ala98].

There are also some complexity issues that need to be studied further in coded multiuser detection. So far the done research has concentrated on studying the performance gains without looking into implementation constraints. The implementation aspects need to be investigated before any deployment decisions can be made.

In the area of soft detection/decoding in mobile terminals there are no significant system issues hindering the deployment of the algorithms studied in this thesis. However, there are issues in the actual implementation, such as the performance of fixed-point implementation. These need to be studied further to evaluate the final feasibility of the proposed algorithms.

Looking at the further utilization of Bayesian networks in the development of new algorithms in the area of communications, there are many potential opportunities. In principle the Bayesian networks can be applied whenever the problem can be described using a system model with random variables. However, currently there are some factors limiting the usability of the Bayesian network approach.

First of all, the behavior of the approximate iterative algorithm in multiply-connected Bayesian networks should be understood better. In particular, theoretical results about the convergence of these algorithms and about propagation of eventual estimation errors are needed. Furthermore, the efficient handling of the continuous-valued random variables is currently possible only in limited case by using different kinds of ad hoc methods. Accordingly, the utilization of Bayesian networks in communications applications is currently almost exclusively limited to cases like channel decoding, where the random variables are essentially discrete. A more uniform way to handle continuous-valued random variables would be very beneficial.

For many important communications applications, the available processing power remains as a limitation also in near future. This applies in particular to the algorithms that are executed in mobile terminals. The use of Bayesian networks in these applications would become much more attractive, if some low-complexity variants of the sum-product algorithm were discovered. The best such candidates are probably some approximate algorithms. Again, the key issue is to understand how the propagation of the calculation errors affects the convergence and accuracy of the results. As was mentioned before, some theoretical results on this would be very useful.

The last requisite for the wider acceptance of the Bayesian network approach is to have a good and easily readable way to present both the networks and the algorithms used. A good effort for a common framework is made in [Fre98], but a more digestible way to use and analyze the Bayesian networks is needed in order to make the approach attractive to a working communications engineer.

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