Novel data detection and channel estimation methods for coded and uncoded CPM signals

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NOVEL DATA DETECTION AND CHANNEL ESTIMATION METHODS FOR CODED AND UNCODED CPM SIGNALS

WANG WENWEN

School of Electrical and Electronic Engineering

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Abstract

Bandwidth limitations and cost considerations are important criteria in mobile communication system developments and these have motivated considerable investigations into continuous phase modulation (CPM) techniques. In recent years, the higher frequency bands have been widely used due to the bandwidth limitations. Thus, fading rates are increasing as the fading rate is proportional to the carrier frequency. Therefore, in modern communication systems, reliable data detection under channels with considerable fading rates poses challenging research problems.

In wireless communications, the transmitted signal is usually affected not only by additive white gaussian noise (AWGN) but also by channel fading. Coding is a typical way to combat fading. The combination of coding with CPM achieves performance gains and bandwidth efficiency at the same time. In order to obtain reliable communication, channel estimation is necessary. Therefore, in this thesis joint data detection and channel estimation schemes are investigated for coded and uncoded CPM signals.

At first data detection for CPM signals transmitted over an AWGN channels is presented. A robust phase estimation based symbol detection algorithm, which does not require the recovery of the modulation index and the alphabet size, is proposed for M-ary full response CPM signals. Secondly, a novel joint data detection and channel estimation algorithm is proposed for CPM signals transmitted over a time-varying flat fading channel. The proposed algorithms mentioned above provide hard outputs only, and therefore, is not suitable for an iterative receiver which needs soft input soft output (SISO) modules. Thus,

thirdly, the hard output module is extended to a novel adaptive SISO module for serially concatenated CPM (SCCPM) signals transmitted over a frequency flat fading channel. Finally, joint data detection and channel estimation for an orthogonal space-time block coded CPM system is investigated. Two objectives are considered: preserving the bandwidth efficiency at the transmitter and the accuracy of data detection at the receiver. It is worth noting that channel estimation problem of orthogonal space-time block coded CPM has not been previously taken into consideration in the literature. Throughout the thesis, extensive simulation results are provided to validate the effectiveness of the proposed algorithms.

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List of Abbreviations

APP	A Posteriori Probability
AWGN	Additive White Gaussian Noise
AR	Auto-Regressive
A-SISO	Adaptive Soft Input Soft Output
A-SISO-BO	Adaptive Soft Input Soft Output with Backward Only
A-SISO-FB	Adaptive Soft Input Soft Output with Forward Backward
A-SISO-FO	Adaptive Soft Input Soft Output with Forward Only
BER	Bit Error Rate
BPSK	Binary Phase Shift Keying
CDMA	Code Division Multiple Access
CPFSK	Continuous-Phase Frequency Shift Keying
CPM	Continuous Phase Modulation
CRB	Cramer-Rao Bound
CSI	Channel State Information
DD	Decision-Directed
DFT	Discrete Fourier Transform
EM	Expectation Maximization
EXIT	Extrinsic Information Transfer
FDE	Frequency Domain Equalization
FHSS	Frequency Hopping Spread Spectrum
FSM	Finite State Machine
GMSK	Gaussian Minimum Shift Keying
GSM	Global System for Mobile Communications
IF	Instantaneous Frequency
KF	Kalman Filtering
LLR	Log Likelihood Ratio
MAP	Maximum a Posteriori Probability
MI	Mutual Information
MIMO	Multiple-Input Multiple-Output
ML	Maximum Likelihood
MLSE	Maximum Likelihood Sequence Estimation
MF	Matched Filter

MMSE	Minimum Mean Square Error
MSE	Mean Square Error
MSK	Minimum-Shift Keying
M-QAM	<i>M</i> -ary Quadrature Amplitude Modulation
OFDM	Orthogonal Frequency-Division Multiplexing
OSTBC	Orthogonal Space Time Block Coded
PAM	Pulse Amplitude Modulation
PSP	Per-Survivor Processing
SCCC	Serially Concatenated Convolutional Code
SCCPM	Serially Concatenated Continuous Phase Modulation
SEP	Single Estimation Processing
SISO	Soft Input Soft Output
SNR	Signal-to-Noise Ratio
SPA	Sum-Product Algorithm
STBC	Space-Time Block Code
STC	Space-Time Code
STTC	Space-Time Trellis Code
VA	Viterbi Algorithm
W-CDMA	Wideband Code Division Multiple Access

List of Notations

r_n	received signal sampled at symbol rate
$\phi(t)$	instantaneous phase
$f(t)$	instantaneous frequency
a_i	i th symbol to be transmitted
$\mathbf{a}_1^N$	transmitted sequence $[a_1, a_2, \dots, a_N]$
$\hat{\mathbf{a}}_1^N$	estimated transmitted sequence $\mathbf{a}_1^N$
$\tilde{\mathbf{a}}_1^N$	possible transmitted sequence $\mathbf{a}_1^N$
$q(t)$	phase response of CPM signals
h	modulation index
$g(t)$	frequency response of CPM signals
L	duration of frequency response
E_b	bit energy
N_0	noise power spectral density
M	alphabet size
T	symbol period
s_n	state at time nT
S_n	states set at time nT
$S_n(s_{n+1})$	states set at time nT in which there has branch connection to s_{n+1}
$b(s_n, s_{n+1})$	branch starts from state s_n to s_{n+1}
$b^{sv}(s_n)$	surviving branch into state s_n
$\lambda(s_n, s_{n+1})$	branch weight of $b(s_n, s_{n+1})$
$\Gamma(s_n)$	state metric of s_k
$s_k(\mathbf{a}_1^k)$	ending state of sequence $\mathbf{a}_1^k$
ST_{+1}	state transition caused by input symbol +1
α	forward coefficient in BCJR algorithm
β	backward coefficient in BCJR algorithm
γ	branch weight in BCJR algorithm
$x(s_k, s_{k+1})$	CPM signal corresponding to state transition from s_k to s_{k+1}
h_k	channel coefficient at time kT
L_o	observation interval

$\hat{\mathbf{a}}_k^{k+L_o-1}(s_{k+L_o-1})$	information sequence corresponding to the survivor path associated with state s_{k+L_o-1}
N_t	size of interleaver
$f_d T$	normalized fading rate
d_{min}	minimum distance
d_B	upper bound of d_{min}
N_B	the length of observation interval required to achieve d_B
$\mathbf{K}_k$	Kalman gain at the k th symbol time
$\mathbf{h}_{k k-1}$	predicted channel state estimate
$\mathbf{h}_{k k}$	updated channel state estimate
$\mathbf{P}_{k k-1}$	covariance of predicted channel state estimate
$\mathbf{P}_{k k}$	covariance of updated channel state estimate
$I(x; y)$	mutual information between two variables x and y

Chapter 1

Introduction

1.1 Motivation

Bandwidth limitations in communication systems have motivated considerable investigations into continuous phase modulation (CPM) techniques [3]. Using CPM and carefully selecting its modulation index h , or length of its frequency impulse L and its alphabet size M , one can get flexible bandwidth-performance tradeoffs. In addition, owing to the constant envelope property of CPM signal, nonlinear amplifiers can be used for cost saving without causing undesired effects on the shape of transmitted signals. Therefore, CPM is suitable for applications with tight transmit power constraints where a linear power amplifier cannot be used; in practice it can be used in underwater cooperative communication with relays, in systems requiring simple and inexpensive transmitters and in digital frequency modulated (FM) land-mobile radio and Bluetooth systems [4]. The favorable properties of CPM are particularly attractive in mobile communication applications which are bandwidth-limited and cost-driven. Due to these properties, CPM has been used in Global System for Mobile Communications (GSM), Bluetooth, IEEE 802.11 Frequency Hopping Spread Spectrum (FHSS) wireless modems, etc [5].

The problem of CPM demodulation in an additive white Gaussian noise (AWGN) channel has been extensively investigated. The optimal demodulation for such problem often

requires maximum likelihood sequence estimation (MLSE) [6] when a hard output is needed and maximum a posterior probability (MAP) detection [7] when a soft output is required. Most of the work on CPM demodulation is based on these two methods. A detailed description of such methods is presented in Chapter 2. The MLSE and MAP demodulations of CPM signals achieve optimal performance but this comes at the price of higher receiver complexity. This has inspired abundant research on reducing the complexity of CPM receivers at the expense of some performance loss. The complexity of the receiver can be split into two parts, namely the number of necessary trellis states and the size of matched filter (MF) banks. In [8] a simplified phase tree based on a frequency pulse shorter than that of the transmitter is used at the receiver, thereby reducing the number of trellis states and that of MFs simultaneously. A widely used complexity reduction method of CPM was proposed in [9], which shows that any binary CPM signal can be expressed as a sum of finite pulse amplitude modulated (PAM) waveforms. The input symbol sequence undergoes a nonlinear operation to generate pseudo-symbols; such symbols are used to decompose a CPM signal representing it as a sum of PAM waveforms. From that point on, the signal can be viewed as a superposition of data-modulated pulses. Based on this decomposition method, Kaleh [10] has proposed a simplified receiver by ignoring some low energy PAM pulses. This detector is based on a small subset of pseudo-symbols and pulses. The reduction in the number of pulses corresponds to a reduction in the size of the matched filter banks, whereas the small subset of pseudo-symbols corresponds to a smaller number of trellis states. Therefore, this method reduces the number of states and the number of matched filters at the same time with a minor performance loss only. Later, Mengali and Morelli have extended the PAM decomposition to multilevel CPM signaling [11].

Most of the existing research on CPM signals in AWGN channels concentrates on reducing the demodulation complexity. Little work has been done on CPM parameter estimation such as estimating its modulation index and its alphabet size. In passive listening

of military applications, the shaping filter at the transmitter may not be known and needs to be estimated for reliable detection [12]. The estimation of symbol timing and carrier frequency of CPM signals has been addressed in [13, 14]. The recovery of symbol timing was discussed in [15]. However, the estimation of the modulation index has not received significant attention and the research work on it is limited and found only in [12, 16]. In general, the widely used Viterbi algorithm (VA), BCJR algorithm (discussed later) and their corresponding simplified algorithms should incorporate other procedures for the modulation index estimation and the alphabet size estimation. Furthermore, it has been shown in [17] that if the modulation index is unknown and estimated at the receiver, the VA performs rather poorly since a small estimation error in the modulation index has a large impact on the performance of CPM demodulation. Motivated by this, we propose a robust demodulation algorithm for M -ary full response CPM signals with $h = 1/M$ in AWGN channels which does not require the recovery of the modulation index and the alphabet size.

In wireless communications, the transmitted signal is usually affected not only by AWGN but also by channel fading; combating fading is one of the most challenging tasks. After illustrating data detection methods of CPM signals in AWGN channels, we then focus our attention on data detection and channel estimation methods in fading channels. In this thesis, it is assumed that the receiver is moving at a constant velocity and an infinite number of reflected waves reach the receiving omnidirectional antenna with a uniformly distributed angle. Therefore, the channel can be modeled as a Rayleigh flat fading channel [18]. In recent years, the use of higher frequency bands has been increasing due to the bandwidth scarcity. Therefore, fading rates have been getting larger (the fading rate is proportional to the carrier frequency) [3]. Therefore, in modern communication systems, how to combat the fading channels with high fading rates is crucial for reliable data detection, which poses challenging research problems.

CPM signals transmitted over fading channels can be demodulated in a noncoherent way; for instance differential detection and limiter-discriminator detection [19] can be

used. In noncoherent demodulation, there is no need for channel estimation. Therefore, the implementation is simple and straightforward. However, the performance of noncoherent techniques exhibits an irreducible error floor which cannot be removed by increasing the signal to noise ratio (SNR). To improve the performance, coherent demodulation is necessary but this requires the channel estimation. There are three types of channel estimation methods. Among these, the simplest one is called pilot-only method and is based on inserting pilot symbols among information symbols. When the channel is constant over time, or fades moderately, this method usually gets good performance (proportional to the length of the training sequence and inversely proportional to the power of environmental noise). However, when channel fading is fast, frequent pilot insertion is required and this reduces the system bandwidth efficiency and results in a loss in data throughput. The second method, known as blind channel estimation, solves the problem of poor bandwidth efficiency since it does not require pilot symbols. Blind channel estimation makes use of the transmitted signal's statistics only and has received significant attention due to its high bandwidth efficiency. However, the convergence rates of most blind methods are slow and depend on the choice of initial values. Moreover, the complexity of blind methods is usually high compared to that of the pilot-only methods. The third method, which combines the advantages of pilot-only methods and blind methods, is called the decision-directed (DD) method. It employs pilot symbols for channel estimation during the pilot transmission and uses the detected symbols (assumed to be correct) for channel estimation during payload transmission. The pilot insertion frequency of the DD methods is smaller than that of the pilot-only methods; this results in improved bandwidth efficiency. Furthermore, the DD methods offer better performance and lower complexity than blind channel estimation methods.

For uncoded CPM signals over time-varying flat fading channels, pilot-only methods have been applied for joint data detection and channel estimation of CPM signals in [20–

22]. In these works, the channel during the payload transmission is interpolated by the estimated channel during pilot transmission. When channel fading is fast, the channel estimate based on pilots quickly becomes unreliable and frequent insertions of pilots are required; this reduces the bandwidth efficiency. Since the DD approach offers a better bandwidth efficiency than the pilot-only method, it has attracted a large amount of research attention. In particular, it has been used for joint data detection and channel estimation of Orthogonal Frequency-Division Multiplexing (OFDM) signals in [23, 24]. Unlike OFDM signals (by which instantaneous data decisions can be obtained), the demodulation of CPM signals incurs a decision delay, which is the time delay between the present time and the time when the most recent decisions are made. This decision delay makes the application of the DD approach to the demodulation of CPM signals not as easy as its application to OFDM signals. The DD approach to CPM demodulation can be divided into two categories: single estimation processing (SEP) [25] and per survivor processing (PSP) [26]. Both of them are based on the VA operating over a trellis diagram. The PSP is a general method to devise MLSE methods in the presence of unknown parameters and it has been applied to the demodulation of CPM signals over unknown flat fading channels in [27, 28]. These two algorithms cannot guarantee the tracking capability and the accuracy of tentative decision at the same time. Novel schemes which can satisfy these two requirements simultaneously are proposed in this thesis.

Note that, in fading channels, even in the presence of a perfect knowledge of channel state information at the receiver, the performance may not satisfy communication requirements. For example, when channel fading is very fast, accurate data detection may not be possible. As a solution, channel coding is introduced to protect the transmitted information sequence from the adverse effects of channel fading by introducing redundancy into the transmitted sequence [29]. It is worth mentioning that channel codes can be classified into two categories: block codes and convolutional codes. In practice, convolutional codes have more applications than block codes.

For convolutional codes, a shift register is used to introduce memory between the sequence of input bits and therefore the encoder output is not only dependent on the input sequence but also on the encoder state. For this reason, the system can be considered as a finite state machine (FSM) [30]. The VA [6], which calculates the ML estimate of the transmitted sequence in a trellis diagram, provides the decoding strategy for the convolutional decoder. Due to the aforementioned advantages of CPM signals, the combination of convolutional codes and CPM modulation could achieve coding gains and bandwidth efficiency at the same time. There are several existing algorithms for the use of convolutional encoded CPM signals in AWGN channels. Coding design has been investigated in [31, 32], while Lindell [33] has derived an upper bound of bit error probability. This has been followed by the study of the detection of convolutional encoded CPM signals in fading channels. When the channel experiences deep fades, error typically occurs in burst, which makes it difficult for the subsequent decoding technique to correct them. An interleaving technique is often used to separate these contiguous errors into independent ones. Code design and error probability was derived for such systems in [34] and [35], respectively. However, only decoding with hard information outputs were considered in these two papers. In [36], a performance gain was obtained by passing soft information instead of the hard one from the output of the demodulator to the convolutional decoder.

The advent of turbo codes brought a new round of research interest [37] on CPM techniques. Here turbo coding is introduced first and then extended to serially concatenated CPM (SCCPM) signals. Turbo coding was first proposed in [38]; turbo encoder consists of two parallel concatenated convolutional codes with an interleaver between them and its performance is close to the Shannon limit [39]. After that, it was discovered that serially concatenated convolutional codes (SCCCs) with an interleaver offer superior performance than turbo codes [40]. Direct decoding of serially or parallelly concatenated convolutional codes involves a high computational complexity. In order to make the receiver simpler, an

iterative receiver was proposed in [38]. The decoder in the iterative receiver is a soft input soft output (SISO) module which can incorporate the a priori information and generate soft output. The decoding procedures of the two decoders in SCCCs are independent and soft information is exchanged in an iterative manner. After some iterations, error performance approaches the optimal one.

It has been shown in [41] that the CPM modulator can be decomposed into a ring convolutional encoder and a memoryless mapper. By replacing the inner encoder of a SCCC with a CPM modulator, an interleaved SCCPM system was formed. It was shown that, with the use of an iterative receiver the SCCPM system achieves comparable performance as turbo codes. In [42], upper bounds for such systems in AWGN channel were derived and the corresponding convergence analysis was given in [43]. The performance of SCCPM with an iterative receiver in fading channels was shown in [44]. However, the promising results were reported under the assumption that the channel information was known at the receiver. The SCCPM systems are typically used in environment of low SNR which makes the channel estimation difficult. There are several existing algorithms for the use of SCCPM with iterative receivers in unknown flat fading channels. For example, the pilot-only algorithm with multiplexing is adopted in [3] for acquiring channel information. Forward-only algorithms and forward backward algorithms which were originally proposed for the decoding of SCCC [45] were analyzed for interleaved SCCPM in [46]. In [1] it has been shown that the forward only algorithms perform better than the forward backward algorithms for SCCPM signals and the convergence analysis of such systems in unknown fading channels has been given considering the phase ambiguities in [2]. The sum-product algorithm (SPA) was adopted at the receiver of SCCPM in [47] and it has been shown to have a promising performance. However, knowing initial conditions at the beginning of each block is assumed and this makes this algorithm inapplicable in most cases.

The benefits offered by convolutional codes always come with a high price in terms of decoder complexity. Therefore, we consider another coding scheme which brings performance gain with a small increase in receiver complexity. Multiple-Input Multiple-Output (MIMO) techniques are one of the most significant breakthroughs in modern communications [48]. A diversity gain in MIMO systems is usually provided by using space-time coding which employs joint encoding crossing multiple transmit antennas and multiple time slots. Information symbols are generated first and then passed through a space-time encoder [48]. Then the encoded symbols are transmitted from multiple antennas simultaneously. The space-time codes can be classified into two main categories: space-time trellis codes (STTCs) and space-time block codes (STBCs) [49].

By distributing a trellis code over multiple antennas and time-slots, space-time trellis codes can provide coding gain as well as diversity gain [50]. Coding gain depends on the minimum distance of the code and the maximal diversity gain is equal to the product of the number of transmit antennas and the number of receive antennas [51]. A multidimensional VA is required for STTC decoding and this makes the demodulation part extremely complicated. The popularity of space-time codes actually starts from the discovery of the STBC in which the encoder encodes the data in a block by block fashion [48]. Since orthogonal STBC (OSTBC) can be decoded through linear processing, it is much simpler than STTC demodulation. To limit the complexity of the receiver, only OSTBC for space-time encoding is considered in this thesis.

Alamouti discovered a simple scheme which accomplishes maximum likelihood (ML) detection by linear processing at the receiver [52]. This scheme is very attractive and has been adopted in the W-CDMA and CDMA-2000 standards [53]. Tarokh *et al.* have extended the Alamouti's two transmit antennas scenario to an arbitrary number of transmit antennas [54]. Linear processing can also be implemented on these codes to perform ML decoding. It is also possible to devise other schemes trading-off orthogonality for transmis-

sion rate. For example, quasi-orthogonal STBCs proposed in [55] can preserve full rate at a cost of a small loss in BER performance together with some extra decoding complexity.

There have been many efforts to extend the space-time codes originally proposed for linear modulation schemes to CPM signals. General STTCs design rules for CPM have been proposed in [56]. Due to the inherent memory in CPM signals and correlation between transmit antennas introduced by STTC, the decoding complexity of the resulting space-time coded CPM is quite high. Moreover, the STTC schemes will change the phase trellis inherent to CPM, which disables the direct application of the existing algorithms. Thus novel receiver structures which are designed specifically for the adopted STTC scheme are needed. Other research results on STTC CPM are available in [57–59], etc. In [56] it has been pointed out that OSTBCs cannot be easily generalized to CPM signals as it is difficult to maintain both orthogonality and phase continuity of the CPM. Note that orthogonal space-time block coded CPM has also been proposed in [60–63].

The orthogonal space-time block coded CPM schemes proposed in the literature assume the availability of accurate channel state information at the receiver. Thus, data detection under unknown channel information for orthogonal space-time block coded CPM signals is still an open problem. In [64, 65], an expectation maximization (EM) based receiver was proposed for space-time block coded OFDM systems. The shortcoming of this approach is that an extra computational overhead is required to obtain the channel statistics. For single antenna channels, EM-based channel estimation has been proposed with CPM signals in [66]. In this thesis, the EM-based channel estimation is extended to the detection of orthogonal space-time block coded CPM.

1.2 Objectives

While a large number of research work have been done on CPM, there is still some room for further improvement to address the challenges of these methods. One of the objectives

of this thesis is to propose a demodulation technique on CPM which does not require the recovery of modulation index and alphabet size. In passive listening, these two parameters may not be known and the existing methods can not be applied. The second objective is to develop algorithms which perform joint data detection and channel estimation for CPM signals transmitted over flat fading channels. The existing SEP and PSP algorithms can not guarantee the tracking capability and the accuracy of tentative decision at the same time. Therefore, we aim at proposing a scheme which can satisfy these two requirements simultaneously. The third objective is to extend demodulator with hard outputs only to a SISO module. Thus, it is suitable for the application of an iterative receiver. The fourth objective is to address the problem of joint data detection and channel estimation for orthogonal space-time block coded CPM signals transmitted over fading channels. Due to the requirement of phase continuity and the associated inherent memory of CPM, the combination of OSTBC with CPM is not as straightforward as with linear modulation schemes. To the best of the author's knowledge, the problem of joint data detection and channel estimation for orthogonal space-time block coded CPM has not been addressed before.

1.3 Original Contributions

In this thesis, several aspects of data detection and channel estimation for coded and uncoded CPM signals have been considered. In Chapter 3 we start with the simplest case of demodulation for full response CPM signals in AWGN channels. Since the existing demodulation methods need to incorporate an additional procedure for modulation index and alphabet size estimation when they are unknown to the receiver, we propose an instantaneous frequency and phase estimation based symbol detection. This method does not require the recovery of the modulation index and the alphabet size. To the best of the author's knowledge, phase estimation based symbol detection has not been reported previously in the demodulation of CPM signals. As the method does not require a prior knowledge of

the modulation index, it is insensitive to its variations. For high level CPM signals with $M > 2$, the performance of the proposed method approaches the optimum provided by the VA endowed with an exact knowledge of the modulation index and the alphabet size. A detailed performance analysis which considers the impact of frequency pulse on BER, the bandwidth efficiency and the effect of larger modulation levels, is also given. The use of instantaneous phase for CPM demodulation and the subsequent performance analysis considering different frequency pulses constitute the contribution of Chapter 3.

A new joint data detection and channel estimation method for uncoded CPM signals in time-varying flat fading channels is proposed in Chapter 4. The proposed method belongs to the category of DD methods which use detected data for channel estimation during payload transmission. The major difficulty of applying a DD approach to CPM signals can be related to the decision delay required for demodulation. There exists a trade-off with respect to the decision delay. In the channel estimation part, increasing the decision delay degrades channel tracking capability while in the data detection part reducing the decision delay affects the accuracy of tentative decisions, and this may result in divergence of the channel tracking trajectories. To solve this problem, the channel over a given observation interval is predicted by modeling it as an AR process. This prediction guarantees zero decision delay and at the same time maintains the accuracy of survivor path selection. Therefore, a decision can be taken for the first symbol of the observation interval in VA. The detected symbol is then fed back for channel updating and state updating in the detection of the next symbol. We also illustrate the advantage of minimum shift keying (MSK) over BPSK in the DD approach due to its ability of mitigating error propagation. The effects of the observation length, prediction order and frame length are discussed in the simulation part. The simulation results show that the proposed scheme performs better than the general PSP and SEP methods.

In Chapter 4, only hard outputs are considered. In Chapter 5, the method in Chapter 4 is extended to an adaptive SISO method to be employed with serially concatenated CPM

signals operating under time-varying flat fading channels. Due to its ability of incorporating a priori symbol probability and the use of soft decision outputs, the accuracy of data detection and channel estimation can be improved through iterations. The convergence behavior of the proposed iterative receiver is also analyzed. Finally, the effect of interleaver size and a comparison among the proposed algorithm, the PSP-based A-SISO forward only (A-SISO-FO) method and SEP based A-SISO method are presented.

In Chapter 6, the techniques for orthogonal space-time block coded CPM are considered. The proposed framework consists of two parts: a novel method for block construction using tail sequences to ensure phase continuity at the transmitter and a joint technique for data detection and channel estimation at the receiver side. First, to ensure phase continuity, a tail sequence is inserted at the end of each block to make the end phase of every block satisfy certain constraints. It is shown that the proposed construction achieves high throughput and the evaluation of the tail sequence can be carried out at one antenna only. Simulation results show that the proposed block construction improves the bandwidth efficiency at the transmitter at the price of an acceptable reduction of data throughput. Then a joint data detection and channel estimation method is proposed for orthogonal space-time block coded CPM signals. To the best of the author's knowledge, this is the first time that the channel estimation problem is discussed for space-time block coded CPM signals. We first derive a ML channel estimator based on the EM algorithm in which the state transition probabilities from the previous iteration are used in the E step as a priori information. It is shown that, due to the assumption that the channels remain constant in one frame and has no memory (flat fading), the complexity of the resulting channel updating is proportional to the frame length. The refined channel estimates are subsequently fed into the BCJR algorithm [7] to evaluate state transition probabilities. Unlike general iterative algorithms, the soft information provided here is state transition probability instead of symbol probability. The E and M steps iterate until satisfactory performance has been achieved. Simulation results show

that the proposed iterative receiver improves the BER performance significantly compared to a non-iterative receiver. After several iterations, the proposed method can achieve the performance with known channel state information when the fading rate is moderate.

1.4 Organization of Thesis

This thesis is organized as follows. Chapter 2 provides the background knowledge of the thesis. Chapter 3 presents a symbol detection algorithm based on the instantaneous frequency and phase estimation and to be employed with full response M -ary CPM signals in AWGN channel. In Chapter 4, a joint data detection and channel estimation algorithm producing hard outputs is proposed. In Chapter 5, the methods in Chapter 4 are extended to a SISO module for SCCPM signals. In Chapter 6, a novel block construction is proposed for ensuring the phase continuity of space-time block coded CPM signals and the problem of joint data detection and channel estimation is addressed. Conclusions and future work are presented in Chapter 7.

Chapter 2

Background Knowledge

Before discussing the problems addressed in the thesis, we introduce some background information which will be useful in subsequent chapters. First CPM, which is the adopted modulation scheme throughout the thesis, is described. Since the channel considered in later chapters is a frequency-flat fading channel, a fading channel model is also introduced. After that data detection under MLSE and MAP criteria in AWGN channels is discussed.

2.1 Continuous Phase Modulation

The complex envelope of a CPM signal can be represented as [67]

$$x(t) = \sqrt{2E_s/T} e^{j\phi(t, \mathbf{a})}, \quad (2.1)$$

where E_s is the average signal energy per symbol and T is the symbol duration time. The signal $x(t)$ has constant envelope and all information is carried in its phase which is given by [67]

$$\phi(t, \mathbf{a}) = 2\pi h \sum_i a_i q(t - iT), \quad (2.2)$$

where h is the modulation index, $a_i \in \{\pm 1, \pm 3, \dots, \pm(M-1)\}$ is the symbol to be transmitted, $\mathbf{a}$ is the transmitted symbol sequence of a_i and $q(t)$ is the phase response of the system which is related to the frequency response $g(t)$ by the relationship

$$q(t) = \int_{-\infty}^t g(\tau) d\tau. \quad (2.3)$$

The frequency pulse is zero outside the time interval $(0, LT)$ and the pulse $q(t)$ is equal to 0 when $t < 0$ and to 1/2 for $t \geq LT$. The integer L is selected as $L = 1$ for full response signaling and $L > 1$ for partial response signaling. We list two widely used frequency pulse shapes: the rectangular (REC) and the raised cosine (RC) shapes, which are given by [68]

$$g_{REC}(t) = \begin{cases} \frac{0.5}{LT} & 0 \leq t \leq LT \\ 0 & elsewhere \end{cases} \quad (2.4)$$

and

$$g_{RC}(t) = \begin{cases} \frac{0.5}{LT}(1 - \cos \frac{2\pi t}{LT}) & 0 \leq t \leq LT \\ 0 & elsewhere \end{cases}, \quad (2.5)$$

respectively. Their corresponding phase response pulses are given by

$$q_{REC}(t) = \begin{cases} 0 & t < 0 \\ \frac{0.5t}{LT} & 0 \leq t < LT \\ 0.5 & t \geq LT \end{cases} \quad (2.6)$$

and

$$q_{RC}(t) = \begin{cases} 0 & t < 0 \\ \frac{0.5t}{LT} - \frac{\sin \frac{2\pi t}{LT}}{4\pi} & 0 \leq t \leq LT \\ 0.5 & t > LT \end{cases}, \quad (2.7)$$

respectively. The information-carrying phase between nT and $(n+1)T$ in Eq. (2.2) can be divided into two terms as

$$\phi(t, \mathbf{a}) = \underbrace{\pi h \sum_{i=-\infty}^{n-L} a_i}_{\theta_n} + 2\pi h \sum_{i=n-L+1}^n a_i q(t - iT). \quad (2.8)$$

We express the modulation index h as $h = k/p$ where k and p are mutually prime integers. According to Eq.(2.8), for $t \in [nT, (n+1)T]$, the information-carrying phase is uniquely defined by the phase state θ_n , the correlative state vector $\{a_{n-1}, a_{n-2}, \dots, a_{n-L+1}\}$ and the present input symbol a_n . The phase state θ_n can take on $2p$ possible values when p is odd and p possible values when p is even. It is well known that the CPM modulator can be described by a finite state machine [44]. As a consequence, it can be presented in

a trellis diagram with associated states and state transitions. The states at the n th symbol interval can be represented as [69]

$$s_n = \{\theta_n, a_{n-1}, a_{n-2}, \dots, a_{n-L+1}\}. \quad (2.9)$$

There are $2pM^{L-1}$ CPM states for odd p and pM^{L-1} for even p . Input symbol a_n with M possible values selects the transition from the state at the n th symbol interval to the one at $(n+1)$ th. Therefore, for each state in the trellis, there exist M input branches and M output branches.

2.2 Flat Fading Channel Model

Based on the assumption that the receiver is moving at a constant velocity and an infinite number of reflected waves arrive at the receiving antenna uniformly from all directions, the power spectrum of the received signal can be expressed via the Jakes' spectrum which is given by [70]

$$S(f) = \begin{cases} \frac{1}{\pi f_d \sqrt{1 - \left(\frac{f}{f_d}\right)^2}} & |f| \leq f_d \\ 0 & \text{elsewhere} \end{cases}, \quad (2.10)$$

where f_d is the maximum doppler frequency. Under this condition, the autocorrelation function of the in-phase and quadrature fading coefficients is given by [71]

$$R_h[n] = J_0(2\pi f_d T n), \quad (2.11)$$

where $f_d T$ is the normalized Doppler frequency and $J_0(\cdot)$ is the zeroth order Bessel function of the first kind. Based on the autocorrelation function in Eq. (2.11), the time-varying fading channel can be modeled as an auto-regressive (AR) process as [71]

$$\mathbf{h}_n = \mathbf{F}\mathbf{h}_{n-1} + \mathbf{w}_n, \quad (2.12)$$

where $\mathbf{h}_n = [h_n, h_{n-1}, \dots, h_{n-N_p+1}]^T$ is an $N_p \times 1$ vector and component h_n is the channel coefficient at time nT . The parameter N_p is the model order which corresponds to the

required model accuracy, whereas

$$\mathbf{F} = \begin{bmatrix} b_1 & b_2 & \cdots & b_{N_p-1} & b_{N_p} \\ 1 & 0 & \cdots & 0 & 0 \\ 0 & 1 & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & 0 & 0 \\ 0 & 0 & \cdots & 1 & 0 \end{bmatrix} \quad (2.13)$$

is a matrix of size $N_p \times N_p$ and $\{b_1, b_2, \dots, b_{N_p}\}$ are the coefficients of the AR model. In addition, $\mathbf{w}_n = [w(n), 0, \dots, 0]^T$ is an $N_p \times 1$ vector and component $w(n)$ is an identically distributed zero-mean complex gaussian random variable. The covariance matrix of $\mathbf{w}_n$ is given by

$$\mathbf{Q}_w = E(\mathbf{w}_n(\mathbf{w}_n)^H) = \begin{bmatrix} \sigma_w^2 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 0 \end{bmatrix}. \quad (2.14)$$

If the coefficients of matrix $\mathbf{F}$ and the noise variance σ_w^2 are given, the current values of channel coefficients $\mathbf{h}_n$ can be represented as a sum of weighted values of the previous channel coefficients $\mathbf{h}_{n-1}$ plus a noise component with variance σ_w^2 . The entries of $\mathbf{F}$ and $\mathbf{Q}_w$ can be evaluated by solving the well known Yule-Walker equation [71], which is given by

$$\mathbf{R}_h \mathbf{b} = \mathbf{r}_h \quad (2.15)$$

where

$$\mathbf{R}_h = \begin{bmatrix} R_h[0] & R_h[1] & \cdots & R_h[N_p-1] \\ R_h[1] & R_h[0] & \cdots & R_h[N_p-2] \\ \vdots & \vdots & \ddots & \vdots \\ R_h[N_p-1] & R_h[N_p-2] & \cdots & R_h[0] \end{bmatrix}, \quad (2.16)$$

$\mathbf{b} = [b_1, b_2, \dots, b_{N_p}]^T$ and $\mathbf{r}_h = [R_h[1], R_h[2], \dots, R_h[N_p]]$. The inverse of $\mathbf{R}_h$ exists in most cases since $\mathbf{R}_h$ is usually positive definite. Thus, the AR model coefficients can be evaluated as

$$\mathbf{b} = \mathbf{R}_h^{-1} \mathbf{r}_h. \quad (2.17)$$

Given the estimated $\mathbf{b}$, σ_w^2 can be computed as

$$\sigma_w^2 = R_h[0] - \sum_{i=1}^{N_p} b_i R_h[i]. \quad (2.18)$$

2.3 Data Detection Methods of CPM Signals over an AWGN Channel

When the CPM signal is transmitted over an AWGN channel, the received signal sampled at the symbol rate can be expressed as

$$r_n = x(n, \mathbf{a}) + v_n, \quad (2.19)$$

where v_n is the contribution of AWGN noise (It is a random variable having zero mean and covariance N_0). Both MAP symbol detection and MLSE provide solutions to the demodulation of CPM and operate over a trellis. The well known BCJR algorithm [7] solves the MAP symbol detection while the VA solves the MLSE in an efficient manner. In uncoded systems, the performance of these two algorithms is almost the same. MAP estimation is closely related to maximum likelihood estimation, but employs an augmented optimization objective which incorporates a priori probability. In concatenated system, an iterative receiver which exchanges soft information between decoders can iteratively achieve near optimum performance with a moderate complexity. Therefore, MAP estimation which exploits the a priori probability and produces soft outputs, is considered for the iterative receiver of the concatenated system.

2.3.1 MLSE via Viterbi Algorithm

Let $\mathbf{a}_1^N = [a_1, a_2, \dots, a_N]$ and $\mathbf{r}_1^N = [r_1, r_2, \dots, r_N]$ denote the M -ary symbol sequence having length N and the received sequence. The MLSE of $\mathbf{a}_1^N$ is given by

$$\hat{\mathbf{a}}_1^N = \arg \max_{\tilde{\mathbf{a}}_1^N \in \mathbf{a}_1^N} \Pr(\mathbf{r}_1^N | \tilde{\mathbf{a}}_1^N), \quad (2.20)$$

where $\hat{\mathbf{a}}_1^N$ and $\tilde{\mathbf{a}}_1^N$ are the estimated and trial $\mathbf{a}_1^N$, respectively, and $\mathbf{a}_1^N$ represents the set of all possible symbol sequences. Due to the AWGN assumption, the optimum detector minimizes the distance

$$\Lambda(\tilde{\mathbf{a}}_1^N) = \sum_{n=1}^N |r_n - x(n, \tilde{\mathbf{a}}_1^N)|^2. \quad (2.21)$$

In ML detection the detector observes the entire received signal and chooses a sequence which minimizes the distance with respect to the received sequence. Since the term $\sum_{n=1}^N |r_n|^2$ and $\sum_{n=1}^N |x(n, \tilde{\mathbf{a}}_1^N)|^2$ are independent of sequence $\tilde{\mathbf{a}}_1^N$, one can, as well, maximize the metric

$$\mu(\tilde{\mathbf{a}}_1^N) = \text{Re} \left(\sum_{n=1}^N r_n x^*(n, \tilde{\mathbf{a}}_1^N) \right), \quad (2.22)$$

where $\text{Re}(x)$ is the real part of x . There are M^N possible transmitted CPM signal sequences. Thus, a comparison needs to be made among M^N possible metrics. This problem of high computational complexity can be solved using the VA. The VA finds the most-likely state transition sequence in a trellis diagram, and is widely used to efficiently detect signals in communication channels with memory. The state of the CPM signal at $t = nT$ has been shown to be $s_n = \{\theta_n, a_{n-1}, a_{n-2}, \dots, a_{n-L+1}\}$. For a given sequence $\tilde{\mathbf{a}}$, Eq. (2.22) can be rewritten as

$$\mu_n(\tilde{\mathbf{a}}) = \text{Re} \left(\sum_{i=1}^n r_i x^*(i, \tilde{\mathbf{a}}) \right) = \mu_{n-1}(\tilde{\mathbf{a}}) + \lambda_n(\tilde{\mathbf{a}}), \quad (2.23)$$

where $\mu_n(\tilde{\mathbf{a}})$ is the metric of the survivor sequence up to time nT and the incremental branch weight is defined as

$$\lambda_n(\tilde{\mathbf{a}}) = \text{Re} (r_n x^*(n, \tilde{\mathbf{a}})). \quad (2.24)$$

For each state in the trellis, there exist M input branches among which the one corresponds to the highest cumulative metric is chosen as the survivor; all the other branches reaching the same state are deleted [6]. The cumulative metric for the next state is increased by the weight of the state transition ($\lambda_n(\tilde{\mathbf{a}})$ in Eq. (2.23)). The cumulative metrics are initialized to 0. The above procedure starts from the first symbol interval and ends at the last

Figure 2.1: Flowchart of the BCJR algorithm

symbol interval of the receive signal. The path which corresponds to the largest cumulative metric at the final state of the whole trellis is the demodulated path.

2.3.2 MAP Symbol Detection via BCJR Algorithm

Unlike MLSE, MAP symbol detection can incorporate the a priori probability of the transmitted symbols. The MAP estimation of a_k is given by

$$\hat{a}_k = \arg \max_{\tilde{a}_k} \Pr(\tilde{a}_k | \mathbf{r}_1^N). \quad (2.25)$$

Different from MLSE which finds the sequence that has the shortest distance with respect to the received sequence, the MAP symbol detection finds symbols which maximize the above probability. Similarly to MLSE, direct calculation of Eq. (2.25) involves a substantial computational complexity; the BCJR algorithm [7] has been proposed to find the MAP data detection efficiently. For simplicity, binary transmission is used to introduce it.

We can obtain the a posteriori probability (APP) of symbol a_k from the APP of state transition by [72]

$$\begin{aligned} \Pr(a_k = 1 | \mathbf{r}_1^N) &= \sum_{ST_{+1}} \Pr(s_k \rightarrow s_{k+1} | \mathbf{r}_1^N) \\ \Pr(a_k = -1 | \mathbf{r}_1^N) &= \sum_{ST_{-1}} \Pr(s_k \rightarrow s_{k+1} | \mathbf{r}_1^N) \end{aligned} \quad (2.26)$$

where ST_{+1} and ST_{-1} are the branches starting from a given state at time k and associated with the input symbols $+1$ and -1 , respectively. The output of the MAP symbol detector is usually the log likelihood ratio (LLR) given by

$$L(a_k) = \log \frac{\sum_{ST_{+1}} \Pr(s_k \rightarrow s_{k+1} | \mathbf{r}_1^N)}{\sum_{ST_{-1}} \Pr(s_k \rightarrow s_{k+1} | \mathbf{r}_1^N)}. \quad (2.27)$$

Following [7], it can be shown that

$$\Pr(s_k \rightarrow s_{k+1} | \mathbf{r}_1^N) = \Pr(s_{k+1} | s_k, \mathbf{r}_1^N) = \gamma(s_k \rightarrow s_{k+1})\alpha(s_k)\beta(s_{k+1}), \quad (2.28)$$

where

$$\gamma(s_k \rightarrow s_{k+1}) = \Pr(s_{k+1}, r_k | s_k), \quad (2.29)$$

$$\alpha(s_k) = \Pr(s_k, \mathbf{r}_1^{k-1}), \quad (2.30)$$

$$\beta(s_{k+1}) = \Pr(\mathbf{r}_{k+1}^N | s_{k+1}). \quad (2.31)$$

α and β are referred to as forward and backward coefficients, respectively. The notations $\mathbf{r}_1^{k-1}$ and $\mathbf{r}_{k+1}^N$ denote the received signal sequences before and after the k th symbol interval, respectively, in the same block. These two coefficients can be evaluated recursively as [7]

$$\alpha(s_{k+1}) = \sum_{s_k \in S_k(s_{k+1})} \gamma(s_k \rightarrow s_{k+1})\alpha(s_k), \quad (2.32)$$

$$\beta(s_k) = \sum_{s_{k+1} \in S_{k+1}(s_k)} \gamma(s_k \rightarrow s_{k+1})\beta(s_{k+1}), \quad (2.33)$$

where $S_k(s_{k+1})$ represents the set of states characterized by branches connecting state s_k to s_{k+1} . Eqs. (2.32) and (2.33) show that the calculation of α and β requires the evaluation of the quantity γ . In AWGN channel, the quantity γ is given by

$$\gamma(s_k \rightarrow s_{k+1}) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{1}{2\sigma^2} |r_k - x(s_k, s_{k+1})|^2\right), \quad (2.34)$$

where $x(s_k, s_{k+1})$ represents the CPM signal during the k th symbol interval associated with the state transition from s_k to s_{k+1} . The flowchart of the BCJR algorithm is shown in Figure 2.1. The BCJR algorithm evaluates through the following steps: First of all, the evaluation of γ is performed on all state transitions for every symbol interval. Secondly, α and β are initialized, and forward recursions based on Eq. (2.32) and backward recursions based on Eq. (2.33) are accomplished for all the states in the trellis diagram. Finally, for a specific a_k , the soft output is generated according to Eq. (2.27).

When there is no a priori information about the symbols, the performance of symbol-by-symbol MAP demodulation and MLSE is almost the same. It was shown in [44] that the complexity of the BCJR algorithm is four times higher than that of the VA. Hence, if hard output is desired, MLSE is more suitable than MAP symbol detection since similar performance is achieved at a lower complexity. Since MAP symbol detection incorporates a priori symbol probability and produces soft outputs, it is essential in iterative processing where MLSE cannot be applied.

2.4 Joint Data Detection and Channel Estimation for CP-M Signals in Unknown Fading Channel

The frequency-flat fading channel will produce a multiplicative distortion affecting the transmitted signal. Therefore, after symbol rate sampling, the received baseband signal over a Rayleigh flat fading channel can be represented as

$$r_n = h_n x(n, \mathbf{a}) + v_n, \quad (2.35)$$

where $x(n, \mathbf{a})$ is the CPM signal, h_n is a zero mean complex Gaussian random variable and v_n is AWGN with variance σ^2 . The characteristics of h_n can be found in Section 2.2. When the channel gain h_n is known, MLSE via the VA and MAP symbol detection via the BCJR algorithm described in Section 2.3 can be used for CPM demodulation. However,

in real communication systems, VA and BCJR algorithm can not be used without tracking the channel. Before deriving the proposed novel algorithms, various existing algorithms which aim at accomplishing joint data detection and channel estimation for CPM signals in unknown flat fading channels are briefly reviewed.

Two widely used methods called PSP and SEP are introduced. They incorporate the channel estimation procedure into the VA. Both of them belong to the category of DD algorithms where the detected data sequence is used as a pilot for estimating the unknown channel. The difference between these two methods is that SEP estimates the channel only once for every symbol interval while in a PSP method, a channel estimate is computed for each state.

In the SEP method, MLSE is performed on the basis of the channel estimate extracted from the previously detected sequence. Note that in the VA, a decision delay is inevitable (the decision delay is the time gap between the present time and the time when the most recent decision is made). It has been shown in [69] that the decision delay (denoted as N_d in the following) is a variable and is usually less than $5L$. $\hat{a}_{k-N_d+1}$ denotes the tentative decision made at time k . The channel estimate at time k in SEP method can be expressed as

$$\hat{h}_k = Z(\mathbf{r}_1^k, \hat{\mathbf{a}}_1^{k-N_d+1}), \quad (2.36)$$

where $\hat{\mathbf{a}}_1^{k-N_d+1} = \{\hat{a}_1, \hat{a}_2, \dots, \hat{a}_{k-N_d+1}\}$ is the detected sequence in the VA, $\mathbf{r}_1^k = \{r_1, r_2, \dots, r_k\}$ represents the received sequence from the first symbol time to the k th symbol time, and $Z()$ defines the relationship between the channel estimate and the detected sequence. In fast time-varying channels, this time delay in data detection reduces the channel tracking capability and hence degrades the performance.

In order to overcome the problem of the decision delay in SEP, the PSP has been proposed in [26] where a channel estimate is evaluated for each state connected by the survivor

branch. Thus, the channel estimate associated with state s_k in PSP can be denoted as

$$\hat{h}_k(s_k) = W\left(\mathbf{r}_1^k, x\left(b^{SV}(s_k)\right)\right), \quad (2.37)$$

where $W()$ is a proper function and $x\left(b^{SV}(s_k)\right)$ is the CPM signal for the surviving branch leading to state s_k . There are pM^{L-1} (or $2pM^{L-1}$) states in a symbol interval; so that we have pM^{L-1} (or $2pM^{L-1}$) channel estimates in each symbol interval when PSP is used. After obtaining $\hat{h}_k(s_k)$, the metrics of the branches leaving s_k can be computed as

$$\lambda(s_k, s_{k+1}) = \left| r_k - x(s_k, s_{k+1}) \hat{h}_k(s_k) \right|^2, \quad (2.38)$$

where $x(s_k, s_{k+1})$ is the CPM signal for the branch transition from state s_k to s_{k+1} . In a PSP-based algorithm, channel estimation is accomplished along the survivor path. Therefore, the branch metrics evaluated in the same interval utilize different estimated channel coefficients.

Chapter 3

Robust Full Response M -ary CPM Receiver in AWGN Channel

In this chapter, a symbol detection method based on the instantaneous frequency and phase estimation is proposed for demodulating full response M -ary CPM signals over an AWGN channel. The method is robust as priori knowledge of the modulation index and the alphabet size is not required and only a unitary decision delay is needed. An efficient instantaneous frequency estimation algorithm that could be used in the implementation of the developed detector is proposed. The performance of the method is analyzed using different frequency pulses. Simulation results show that, for higher order CPM signals with $M > 2$, the performance of the proposed method approaches that of the optimum performance provided by the VA endowed with the knowledge of the modulation index and the alphabet size. The method is also computationally attractive when M is large.

3.1 Introduction

A CPM signal is a frequency modulated signal with continuous phase among adjacent symbols. As mentioned in Chapter 1, the bandwidth and power efficiency of CPM result from its continuous phase and constant envelope. Signals having a constant envelope but time varying instantaneous phase such as CPM signals are common in many other engineering

disciplines, e.g. radar and sonar signal processing. Such signals belong to the broader category of frequency modulated (FM) signals and can be characterized using the instantaneous frequency (IF), which is the time derivative of the instantaneous phase [73]. IF estimation has been extensively investigated in the past few decades and many efficient IF estimation techniques have been developed based on the peak location of the Discrete Fourier Transform (DFT) [73, 74]. A simpler, computationally efficient, autocorrelation based IF estimation algorithm has been proposed in [75]. Given an estimate of the IF, phase estimation is straightforward. This chapter discusses a combined instantaneous frequency and phase estimation receiver for demodulating CPM signals.

The optimum demodulation of CPM signals over AWGN channels often requires MLSE based on the VA [6]. Several suboptimal demodulation methods have been introduced in Chapter 1 to reduce complexity at the expense of some performance loss. However, these methods assume that the modulation index and the alphabet size are known. In passive listening for military use, the parameters related to the modulation scheme may not be known. This is also essential in an underwater communication environment where the signals need to be re-sampled for the relative motion compensation of receivers [76]. Alternatively, receiver filters need to be accurately re-sampled. Modulation index estimation has been investigated in [12, 16], where higher order statistics of the received signal are utilized for parameter estimation. Thus, the existing demodulation methods should incorporate another procedure for modulation index and alphabet size estimation if these parameters are unknown to the receiver. Furthermore, in [17] it has been shown that if the modulation index is unknown and estimated at the receiver, the VA performs rather poorly since a small estimation error in the modulation index has a large impact on the performance of CPM demodulation.

In this chapter, a receiver which does not require the recovery of modulation index and alphabet size for full response M -ary CPM signals with $h = 1/M$ or $h = 1 - 1/M$ is

proposed. The proposed method is based on IF and phase estimation. The schemes of using frequency estimation for the symbol detection of CPM signals have been reported in [77–79]. However, their performances are not satisfactory since the information carried on the phase is not considered. To the best of author’s knowledge, this is the first time that the DFT based instantaneous frequency and phase estimation has been used in the CPM demodulation. As the conventionally used DFT peak search based IF estimation is computationally intensive [80], this chapter (in Section 3.4.2) also proposes a novel efficient IF estimation method suitable for CPM transmission. Detailed performance analysis is provided which shows that for full response M -ary CPM schemes, instantaneous phase estimation provides an efficient and robust demodulation method. Performance analysis using different frequency pulses and the bit error rate (BER) comparisons between the proposed method and the VA with known modulation index and alphabet size are also given. Such a detailed comparison of the use of IF estimation for CPM demodulation is not available in the literature.

3.2 IF Estimation and Phase Estimation

Consider a constant amplitude frequency modulated signal $r(t)$ in the presence of an additive complex white Gaussian noise $v(t)$, i.e.,

$$r(t) = \xi e^{j\phi(t)} + v(t), \quad (3.1)$$

where $\phi(t)$ is the instantaneous phase. The constant term ξ is the complex signal amplitude. The signal-to-noise ratio (SNR) for the signal in Eq. (3.1) is defined as $SNR = |\xi|^2/\sigma^2$, where σ^2 is the noise variance. The instantaneous phase can be related to the signal instantaneous frequency $f(t)$ as

$$f(t) = \frac{1}{2\pi} \frac{d\phi(t)}{dt}. \quad (3.2)$$

When the IF is slow varying, an efficient way to estimate $f(t)$ is to use the peak of the DFT, which also meets the Cramer-Rao bound (CRB) for frequency estimation [80, 81]. If $\hat{f}_0$ is the estimated IF during time interval 0 to T , it is easy to attain the initial phase and end phases at time 0 and T as

$$\hat{\phi}(t) |_{t=0} = \frac{1}{j} \log \left\{ \frac{1}{T} \int_0^T r(t) e^{-j2\pi \hat{f}_0 t} dt \right\} \quad (3.3)$$

and

$$\hat{\phi}(t) |_{t=T} = \frac{1}{j} \log \left\{ \frac{1}{T} \int_0^T r(t) e^{-j2\pi \hat{f}_0 t} dt \right\} + 2\pi \hat{f}_0 T, \quad (3.4)$$

respectively. After sampling, we denote the number of samples in one symbol period as N_s . It has been shown in [80] that the mean square error (MSE) of frequency estimation is $\sigma_{IF}^2 = 3/(2\pi^2 N_s^3 \times SNR)$ if a DFT is used for frequency estimation. The corresponding MSE of phase estimation via Eq. (3.3) and Eq. (3.4) is $\sigma_\phi^2 = 4/(N_s \times SNR)$. We relate the SNR to the bit energy to noise spectral density ratio E_b/N_0 as

$$SNR = \frac{E_s}{T\sigma^2} = \frac{E_b (\log_2 M)}{TN_0 f_s} = \frac{(\log_2 M)}{N_s} \left(\frac{E_b}{N_0} \right). \quad (3.5)$$

Then we have the CRB of IF and phase estimation as

$$\sigma_{IF}^2 = \frac{3}{(\log_2 M) 2\pi^2 T^2} \left(\frac{N_0}{E_b} \right) \quad (3.6)$$

and

$$\sigma_\phi^2 = \frac{4}{(\log_2 M)} \left(\frac{N_0}{E_b} \right), \quad (3.7)$$

respectively. This shows that, if M increases, more accurate frequency and phase estimates can be obtained.

3.3 Full Response CPM Signals

Similarly to the signal in Eq. (3.1), when the CPM signal is transmitted in an AWGN channel, the received signal can be expressed as

$$r(t) = \sqrt{\frac{E_s}{T}} e^{j\phi(t, \mathbf{a})} + v(t). \quad (3.8)$$

As noted earlier, E_s is the average signal energy per symbol, T is the symbol duration time and $\mathbf{a}$ is the transmitted symbol sequence. The information of the CPM signal is carried by $\phi(t, \mathbf{a})$ and a detailed description of this representation has been presented in Chapter 2. In this chapter, full response ($L = 1$) transmission is considered. Two types of frequency pulse shapes are discussed first: the rectangular (REC) and the raised cosine (RC) shapes. They are given by Eq. (2.4) and (2.5) with $L = 1$, respectively. Full response CPM with rectangular frequency shape is also known as continuous phase frequency shift keying (CPFSK). Using the frequency pulses of Eqs. (2.4) and (2.5), the transmitted REC and RC instantaneous phases in the period ($0 \leq t \leq T$) can be expressed, respectively as

$$\phi(t) = ha_n \int g(t) dt = \begin{cases} 0 & t < 0 \\ (2\pi t)f_{av} & 0 \leq t \leq T \\ 2\pi T f_{av} & t > T \end{cases} \quad (3.9)$$

and

$$\phi(t) = \begin{cases} 0 & t < 0 \\ (2\pi t - T \sin(2\pi t/T))f_{av} & 0 \leq t \leq T \\ 2\pi T f_{av} & t > T \end{cases}, \quad (3.10)$$

respectively, where f_{av} is the average frequency and given by

$$f_{av} = 0.5ha_n/T. \quad (3.11)$$

3.4 IF Estimation for M -ary Full Response CPM

For the purpose of later discussion, IF estimation using a moving DFT is considered in this section. In implementations, other efficient IF estimation methods can also be used for reducing complexity [75]. Both rectangular and raised cosine frequency pulses are considered in the following discussion.

Figure 3.1: Transmitted symbol and the estimated normalized IF for $SNR=20$ dB, Quaternary CPFSK signalling with $h = 0.9$ is assumed.

3.4.1 IF Estimation Using a Moving DFT

The sliding window DFT is a well known computationally efficient method for frequency estimation. It performs an N -point DFT within a sliding window first. Then the time window is advanced one sample and a new N -point DFT is evaluated. The benefit of this method is that the old DFT values are utilized for the evaluation of new DFT [82]. As an example, Figure 3.1 shows the estimated IF (normalized) using the DFT of a sliding window when the frequency pulse is a full response rectangular pulse with $M = 4$ (Quaternary CPFSK) and $h = 0.9$ [79]. Figure 3.2 shows the eye-diagram resulting from the IF estimate of a quaternary RC transmission. The DFT outputs can be used for symbol interval estimation and if necessary, for synchronization of the receiver. The alphabet size M and the frequency pulse can also be estimated from Figures 3.1 and 3.2, although such

Figure 3.2: Eye diagram resulting from the IF in an RC transmission with $M = 4$, $L = 1$, $E_b/N_0 = 20$ dB, $h = 0.8$ is assumed. (T is the symbol duration time)

estimation are not presented in this thesis. Note also that, for better clarity, a high E_b/N_0 value is used in Figures 3.1 and 3.2.

3.4.2 IF Estimation Using an Efficient DFT

The above introduced IF estimation for symbol detection of CPFSK signals requires a DFT peak search which incurs a heavy computational complexity. Therefore, efficient DFT peak search algorithms are essential for reducing the computational burden on the CPM demodulator. We start with the correlation based algorithm proposed in [75] for frequency estimation. It initially makes a coarse search for the DFT peak value and then utilizes this in the autocorrelation for the next fine peak search. By doing so, the MSE of the frequency estimation will approach the CRB when the IF is constant as in CPFSK. (The CRB requires evaluating the Fisher information matrix for the frequency pulses in Eqs. (2.4) and (2.5). Please refer to [80] and [81] for further details.) However, when the IF is not constant

Figure 3.3: The MSE of IF estimation using an efficient DFT for octal CPFSK

within the symbol period, as in RC transmission, this method of IF estimation fails to approach the CRB. Based on the frequency pulse, here a novel method which approaches CRB through iterations is proposed. The method is described using following two steps.

STEP 1- DFT coarse search:

Let $R(k)$ and $\rho(t)$ be the N -point DFT and the autocorrelation of signal $r(t)$ of Eq. (3.8) referring to the observation interval $[0, T]$, respectively. As noted earlier, N_s is the number of samples per symbol (typically small, 8 or 16). The autocorrelation can be obtained through an inverse Fourier transform of the squared DFT.

- (i) Let f_0 be an initial estimate for f_{av} of Eqs. (3.9) and (3.10) obtained using a coarse search on the magnitude of $R(k)$.

STEP 2- Iteration for bias compensation:

- (i) Using the estimate for f_{av} (initially f_0) to evaluate the phase function, $\phi(t)$ using Eqs. (3.9) or (3.10).

Figure 3.4: The MSE of IF estimation using an efficient DFT for octal full response CPM with raised cosine frequency shape.

- (ii) Evaluate a bias removed autocorrelation function $\rho_i(t)$ as the autocorrelation of $r(t)e^{-j\phi(t)}$.
- (iii) Use $\rho_i(t)$ to obtain an improved estimate for f_{av} , as f_i given by,

$$f_i = f_0 + \frac{1}{2\pi} \tan^{-1} \left(\int \rho_i(t) e^{-j\phi(t)} \right). \quad (3.12)$$

Iterate step 2 a few times for improving the IF estimation accuracy.

Figure 3.3 shows the MSE of the proposed DFT based IF estimation method described above for octal CPFSK. The estimation procedure approaches CRB after the first iteration. The performance of Figure 3.4 is obtained using a modulation scheme as same as that of Figure 3.3 except that the rectangular frequency pulse shape is replaced by a raised cosine shape. In Figure 3.4, the optimal performance is approached after three-four iterations.

The estimated frequency f_{av} in Eq. (3.11) allows us to detect the transmitted symbol a_n . Performance results on the use of IF for symbol detection of CPM signals have been

illustrated in [77–79]. As the IF estimation could be used for any modulation index without prior knowledge of it, if needed, the modulation index h could also be estimated using f_{av} . Note that, if the modulation scheme has an irrational modulation index and consists of quaternary or octal transmissions, the number of states and branches of the trellis diagram in the VA could be quite large. Unlike the VA, the IF based symbol detector has a similar computational complexity with any modulation index and alphabet size. However, the bit error performance offered by the IF based symbol detection is not satisfactory since it does not use the information at the phase [79]. As phase can be easily estimated once the frequency is estimated, in the following section, it will be shown that via differential encoding and phase estimation, the performance of the demodulator can be improved.

3.5 Pre-Coded Signals and Phase Estimation Based Symbol Detection

For an M -ary transmission, when $h = 1/M$ or $h = 1 - 1/M$, differential encoding on information symbol c_n is given by

$$a_n = 2 \left(c_n + (M - 1)c_{n-1} \right)_{\text{mod } M} - M + 1, \quad (3.13)$$

where $c_n \in \{0, 1, \dots, M - 1\}$ and $a_n \in \{\pm 1, \pm 3, \dots, \pm(M - 1)\}$. The encoded symbol a_n is then sent to a CPM modulator. Differential encoding on M -ary full response CPM with $h = 1/M$ or $h = 1 - 1/M$, which makes the transmitted data information shift from frequency to phase, can provide better performance than using the frequency estimation method described above. As stated before, the phase of a CPM signal in the current symbol interval depends on all the previous input symbols. The differential encoding removes the long memory and, as a result, each input symbol affects its nearest two symbol intervals only, and a single decision delay is sufficient for optimum estimation.

Therefore, if differential encoding is used, only two symbol intervals are required for making a decision. Suppose we are interested in estimating the instantaneous phase at $t = T$. According to Eqs. (3.3) and (3.4), the evaluation of the start and end phases of the interval $[0, T]$ can be obtained based on the estimated frequency during that interval. Using the same approach the estimates

$$\hat{\phi}(t)\Big|_{t=T} = \frac{1}{j} \log \left\{ \frac{1}{T} \int_T^{2T} z(t) e^{-j\hat{\phi}_1(t)} dt \right\} \quad (3.14)$$

and

$$\hat{\phi}(t)\Big|_{t=T} = \frac{1}{j} \log \left\{ \frac{1}{T} \int_0^T z(t) e^{-j\hat{\phi}_0(t)} dt \right\} + 2\pi\hat{f}_0T \quad (3.15)$$

can be obtained using the data in intervals $(0 < t < T)$ and $(T < t < 2T)$, respectively. $\hat{f}_0$ and $\hat{f}_1$ are the average frequencies (f_{av}) estimated using the data in the intervals $(0 < t < T)$ and $(T < t < 2T)$, respectively. For the two intervals, based on $\hat{f}_0$ and $\hat{f}_1$, the phase response $\hat{\phi}_0$ and $\hat{\phi}_1$ can be evaluated using Eqs. (3.9) and (3.10). Combining Eqs. (3.14) and (3.15), the estimated phase at $t = T$, based on the data referring to two symbol intervals is obtained as

$$\begin{aligned} \hat{\phi}(t)\Big|_{t=T} &= \frac{1}{2j} \log \left\{ \frac{1}{T} \int_T^{2T} z(t) e^{-j\hat{\phi}_1(t)} dt \right\} + \\ &\quad \frac{1}{2j} \log \left\{ \frac{1}{T} \int_0^T z(t) e^{-j\hat{\phi}_0(t)} dt \right\} + \pi\hat{f}_0T. \end{aligned} \quad (3.16)$$

Since there are only 2 phases (0 and π) in binary transmission ($M = 2$), when using pre-coded signals, the detection is performed using either the real or the imaginary part of the received signals. This is expected to provide a 3 dB performance improvement over that of the use of the complex signal [69]. Eq. (3.16) is then modified for $M = 2$ as

$$\begin{aligned} \hat{\phi}(t)\Big|_{t=T} &= \frac{1}{2j} \log \left\{ \frac{1}{T} \int_T^{2T} z(t) \cos(\hat{\phi}_1(t)) dt \right\} + \\ &\quad \frac{1}{2j} \log \left\{ \frac{1}{T} \int_0^T z(t) \cos(\hat{\phi}_0(t)) dt \right\} + \pi\hat{f}_0T. \end{aligned} \quad (3.17)$$

3.6 Simulation Results

3.6.1 Bit Error Rate Performance

Figure 3.5 shows the BER performance of the proposed symbol detector based on phase estimation for full response CPM signals with $h = 1/M$. The optimal performances provided by the VA endowed with an exact knowledge of the modulation index and the alphabet size are also shown for comparison. The performance was evaluated using a simulated sample CPM signal with 8 samples per symbol. Gaussian noise with variance corresponding to Eq. (3.7) was added to obtain the required E_b/N_0 value. Four alphabet sizes are considered: $M = 2, 4, 8, 16$. Note that the VA uses the entire received sequence and therefore, requires a long observation period. If a short observation period is used, the VA usually performs worse. For $M > 2$, the performance of the proposed detector gets close to that of the VA (a loss of 0.5 dB is found). The performance also improves as M increases. However, this improvement comes at the price of a reduction in the bandwidth efficiency. The greatest strength of the proposed phase estimation based symbol detection is that it does not require the recovery of the modulation index and the alphabet size. However, there are several weaknesses as well. The proposed method only applies to full response CPM with $h = 1/M$ or $h = 1 - 1/M$. Furthermore, the proposed method incurs a higher computational complexity than the conventional VA, when the alphabet size is small, and the size of the trellis diagram is small.

3.6.2 Impact of the Frequency Pulse

In order to determine the impact of the frequency pulse shape on the performance and also evaluate the behavior of the frequency estimation algorithm proposed in Section 3.4, two other frequency pulses are considered. The pulses are selected in a way that they have different peak values at the mid-point of symbol period. The first pulse is the half-cycle

Figure 3.5: The performance of phase estimation based symbol detection and that of VA for full response RC CPM with $h = 1/M$

sinusoid (HCS) defined as

$$g(t) = \begin{cases} \frac{\pi}{4LT} \sin\left(\frac{\pi t}{LT}\right) & 0 \leq t \leq LT \\ 0 & \text{elsewhere} \end{cases} \quad (3.18)$$

The second selected pulse, called modified pulse (MOD), is given by

$$g(t) = \begin{cases} \frac{2\pi}{LT} \left[\sin\left(\frac{\pi}{2} \times \frac{t}{LT}\right) \right]^3 \cos\left(\frac{\pi}{2} \times \frac{t}{LT}\right) & 0 \leq t \leq \frac{LT}{2} \\ \frac{2\pi}{LT} \left[\cos\left(\frac{\pi}{2} \times \frac{t}{LT}\right) \right]^3 \sin\left(\frac{\pi}{2} \times \frac{t}{LT}\right) & \frac{LT}{2} \leq t \leq LT \\ 0 & \text{elsewhere} \end{cases} \quad (3.19)$$

The four different frequency pulses (REC, HCS, RC, and MOD) used in the CPM transmission schemes are shown in Figure 3.6. The peak values of these pulses are $(\frac{1}{2LT}, \frac{\pi}{4LT}, \frac{1}{LT}, \frac{\pi}{2LT})$, respectively. Note that they have the same average frequency $(\frac{1}{2LT})$. Figures 3.7 and 3.8 show the frequency estimation performances and it is seen that, as the peak value at mid-point of pulse increases, the frequency estimation requires more iterations to reach the CRB. The HCS approaches CRB in about 3 iterations while the MOD pulse requires around 6 iterations.

Figure 3.6: Four different frequency pulses.

 Figure 3.7: MSE vs E_b/N_0 for the proposed frequency Estimator for an octal HCS pulse.

Figure 3.8: MSE vs E_b/N_0 for the proposed frequency estimator for an octal modified pulse.

Table 3.1: Comparison of R/W vs E_b/N_0 for REC and RC Transmission. (Symbol error rate is 10^{-5})

METHOD	R/W	E_b/N_0 (Optimum)	E_b/N_0 (Ph)
M=2 REC(MSK)	1.62	9.55	10.3
M=4 REC	2.95	11.3	12.5
M=8 REC	4.47	15.5	16.4
M=16 REC	5.88	20.2	21.2
M=2 RC	1.37	9.55	11.0
M=4 RC	2.56	10.6	11.2
M=8 RC	3.74	14.4	14.7
M=16 RC	5.04	19.1	19.4

3.6.3 Bit Rate per Bandwidth on Different Transmission Schemes

In order to compare different transmission schemes, we have evaluated the performance on bit rate per bandwidth (R/W) [83] against the energy of transmission per bit, E_b , over noise power spectral density N_0 (E_b/N_0). The effective bandwidth (B_{eff}) for a given

Table 3.2: Comparison of R/W vs E_b/N_0 for HCS and MOD Transmission. (Symbol error rate is 10^{-5})

METHOD	R/W	E_b/N_0 (Optimum)	E_b/N_0 (Ph)
M=2 HCS	1.44	9.55	10.8
M=4 HCS	2.73	10.8	11.6
M=8 HCS	3.94	14.5	15.1
M=16 HCS	5.17	19.4	19.8
M=2 MOD	1.28	9.55	11.3
M=4 MOD	2.45	10.4	10.9
M=8 MOD	3.55	14.1	14.5
M=16 MOD	4.68	18.7	19.2

transmission can be evaluated as

$$B_{eff} = \frac{\int S(f) df}{s(0)} \quad \text{and} \quad R/W = 1/B_{eff}, \quad (3.20)$$

where $S(f)$ is the power spectrum of the transmitted signal. The inverse of the effective bandwidth provides the spectral efficiency (R/W) was listed in Table 3.1 for M -ary REC and RC transmissions. In this table some energy efficiency results referring to phase estimation based symbol detection and the VA (endowed with known modulation index and alphabet size) are shown (they are denoted by “Ph” and “Optimum”, respectively); E_b/N_0 here represents the required value to obtain a symbol error rate equal to 10^{-5} . Table 3.2 shows the R/W vs E_b/N_0 performance for the HCS and the MOD pulses. These results show that the performance of HCS is between that of the REC and RC transmissions; moreover the MOD pulse performs better than the other schemes in terms of the E_b/N_0 value, but at a lower R/W .

3.7 Summary

In this chapter a method for phase estimation based symbol detection to be employed with full response M -ary CPM signals had been proposed. Phase estimation is attained via

instantaneous frequency estimation which is based on short-duration DFT and autocorrelation. Compared with existing algorithms, the proposed method is robust since it does not require a priori knowledge of the modulation index and the alphabet size. Simulation results show that it losses 0.5 dB only compared to a VA with known modulation index and alphabet size. Since the computational complexity of the proposed method is independent of alphabet size M , the method is attractive to use with large values of M .

Transmitted signals affected by AWGN only are the simplest case in communications. In wireless communications, apart from the effect of noise, signals will suffer from channel fading effects also. The flat fading channel will cause a multiplicative distortion affecting the transmitted signals. In the method proposed in this chapter, to improve the performance of the frequency estimation based symbol detection, differential encoding had been adopted; this shifts the information from frequency to phase. As the tolerance for the multiplicative fading distortion of a phase modulated signal is weaker than that of a frequency modulated signal, the proposed method cannot perform well in fading channels. In the following chapters, new demodulation methods incorporating channel estimation will be investigated to combat fading.

Chapter 4

Joint Data Detection and Channel Estimation for Uncoded CPM

In this chapter the problem of joint data detection and channel estimation for CPM signals transmitted over a time-varying frequency-flat fading channel is addressed. In order to allow the implementation of coherent demodulation, channel estimation through channel tracking is commonly adopted in time-varying channels. The proposed method here is based on a decision directed (DD) approach for channel tracking. Due to the inherent memory in CPM, the difficulty of applying a DD approach can be related to the decision delay required in CPM demodulation; such a delay degrades the channel tracking capability. To solve this problem, we propose a method in which the channel over a given observation interval is predicted via a Kalman predictor for data detection. Then the detected data is utilized in Kalman filter (KF) updating. We also illustrate the advantage of MSK over BPSK in using the DD approach; this advantage is due to the ability of the proposed method to eliminate error propagation. Error analysis of the proposed algorithm has been conducted and simulation results show that the proposed algorithm provides improved performance in terms of BER over commonly used algorithms, such as per-survivor processing (PSP) [26] and single estimation processing (SEP) [25].

4.1 Introduction

Over the years, various methods for joint data detection and channel estimation have been developed. In [84] joint data detection and channel estimation is accomplished via a super-trellis which involves a large memory in the demodulator; in this case channel estimation is performed for every state. The cost for the excellent performance of this method is its relatively high complexity caused by the exponentially increasing number of states. In [20–22] channel coefficients during payload transmission are derived from interpolating the channel estimated by means of pilots. When channel fading is fast, this kind of pilot-only channel estimation method requires a frequent insertion of pilot symbols and this reduces the bandwidth efficiency. Another typical method for joint data detection and channel estimation is the DD approach that employs pilots for channel estimation during pilot transmission and uses detected symbols for channel tracking during payload transmission. Since the DD approach is simpler than super-trellis method and achieves more bandwidth efficiency over the pilot-only approach, it has attracted a large amount of research attention.

The DD approach has been used for joint data detection and channel estimation of Orthogonal Frequency-Division Multiplexing (OFDM) signals in [23, 24]. Unlike with OFDM signals (in which instantaneous data decisions can be obtained), the demodulation of CPM signals entails a decision delay, which is the time delay between the present time and the time when the most recent decisions are made. This decision delay makes the application of the DD approach to CPM signals not as easy as its application to OFDM signals. Existing DD approaches to CPM demodulation fall into two categories: the SEP algorithm and the PSP algorithm. Both of them are based on the use of Viterbi algorithm (VA) operating over a trellis diagram. In SEP algorithm, a decision delay is inevitable and this results in poor tracking performance in fast-fading channels. Channel tracking in PSP algorithm is operated for every state via the survivor branch on that state which ensures high tracking capability. However, the selection of the survivor branch may not be accurate

due to the zero decision delay. There exists a selection accuracy trade off with respect to the decision delay. In channel estimation part, increasing decision delay degrades channel tracking capability whereas in data detection part, reducing it worsens the accuracy of the tentative decision, leading to potential divergence of the channel tracking trajectories. We address this problem of the DD approach in a different way. A KF, that predicts the channel coefficients over a given observation interval, is incorporated into the DD approach such that the effect of decision delay is greatly reduced. Compared with the PSP and SEP algorithms, the proposed algorithm guarantees the accuracy in data decisions and the capability of channel tracking simultaneously. The chapter also provides an approximated BER of the proposed algorithm. Simulation results show that the proposed algorithm performs better than the above mentioned two benchmark algorithms.

The notations adopted for the trellis diagram are as follows: $\mathcal{S}_k$ is the set of states at the k th instant and $s_k \in \mathcal{S}_k$ is one of the pM^{L-1} or $2p^{L-1}$ states in $\mathcal{S}_k$. $\lambda(s_k, s_{k+1})$ denotes the branch metric of branch connecting states s_k and s_{k+1} ; $\Gamma(s_k)$ is the state metric associated with the state s_k . There is a one-to-one correspondence between the branch and the CPM signal and $x(s_k, s_{k+1})$ denotes the CPM signal associated with the branch connecting states s_k and s_{k+1} .

4.2 The Proposed Algorithm

As stated earlier there exists a conflict requirement on the decision delay. In channel tracking part, a short decision delay is required while in data detection part, a long decision delay is needed. The PSP and SEP algorithms cannot guarantee the accuracy of tentative decisions and the capability of channel tracking at the same time. The proposed demodulator aims in solving this conflict. Fig. 4.1 shows the flowchart of the proposed algorithm. Channel over a given observation interval is predicted via the modeling of the channel as

Figure 4.1: Flowchart of the proposed algorithm

an auto regressive (AR) process. Then a decision is made at the first symbol of the observation interval in the VA. The detected symbol is fed back for channel updating and state updating for the detection of the next symbol. This prediction over an interval guarantees a high tracking capability and at the same time maintains the accuracy of the survivor path selection. The proposed algorithm consists of two parts: a truncated VA as described in Section 4.2.1 and a DD KF described in Section 4.2.2. The selection of an important parameter, the observation interval (L_o in Fig. 4.1), for the proposed algorithm is discussed in Section 4.2.3.

4.2.1 Truncated Viterbi Algorithm

Define three vectors in a block $\mathbf{a}_1^{N_b} = [a_1, a_2, \dots, a_{N_b}]^T$, $\mathbf{r}_1^{N_b} = [r_1, r_2, \dots, r_{N_b}]^T$, $\mathbf{h}_1^{N_b} = [h_1, h_2, \dots, h_{N_b}]^T$ where N_b is the block length, $\mathbf{a}_1^{N_b}$ and $\mathbf{r}_1^{N_b}$ represent the input data sequence at the transmitter and the received sequence at the receiver, $\mathbf{h}_1^{N_b}$ is a vector of time-varying flat fading channel coefficients. If $\mathbf{h}_1^{N_b}$ is known, the maximum likelihood (ML) estimation of a_k based on the corresponding received sequence $\mathbf{r}_1^{N_b}$ can be evaluated as

$$\hat{a}_k = \arg \max_{\tilde{\mathbf{a}}_1^{N_b} : \tilde{a}_k} \Pr(\mathbf{r}_1^{N_b} | \tilde{\mathbf{a}}_1^{N_b}, \mathbf{h}_1^{N_b}) \quad (4.1)$$

where $\hat{a}_k$ represents the estimated a_k and $\tilde{\mathbf{a}}_1^{N_b}$ represents all the possible transmitted sequences of $\mathbf{a}_1^{N_b}$, $\tilde{\mathbf{a}}_1^{N_b} : \tilde{a}_k$ are possible transmitted sequences $\mathbf{a}_1^{N_b}$ which contain a_k at the k^{th} symbol. When $\mathbf{h}_1^{N_b}$ is unknown, one must evaluate the conditional probability density function over the probability density function of $\mathbf{h}_1^{N_b}$. However, it is not easy to perform. Another way is via the DD approach which estimates the unknown parameter and then to use it in determining the probability. The decision criterion becomes

$$\hat{a}_k = \arg \max_{\tilde{\mathbf{a}}_1^{N_b} : \tilde{a}_k} \Pr(\mathbf{r}_1^{N_b} \mid \tilde{\mathbf{a}}_1^{N_b}, \hat{\mathbf{h}}_1^{N_b}) \quad (4.2)$$

where $\hat{\mathbf{h}}_1^{N_b}$ is the estimated channel coefficient. Since there are M^{N_b} possible sequences of $\tilde{\mathbf{a}}_1^{N_b}$, the computational burden for the direct evaluation of Eq. (4.2) is relatively high and the decision can only be made after the whole block has been received. In order to solve the problem of long decision delays, we use the fact that there is a high chance that the survivor up to time $(k + L_o - 1)$ will be the same as the one up to time k when the time spacing L_o is sufficiently large [69]. Therefore, for the k^{th} symbol decision, the decision criterion can be approximated as

$$\hat{a}_k = \arg \max_{\tilde{\mathbf{a}}_1^{k+L_o-1} : \tilde{a}_k} \Pr(\mathbf{r}_1^{k+L_o-1} \mid \tilde{\mathbf{a}}_1^{k+L_o-1}, \hat{\mathbf{h}}_1^{k+L_o-1}) \quad (4.3)$$

Note that in Eq. (4.3) the k^{th} symbol decision is made when the trellis search up to time $(k + L_o - 1)$. This decision delay ensures the accuracy of symbol detection. Therefore, the previously detected sequence $\hat{\mathbf{a}}_1^{k-1} = [\hat{a}_1, \hat{a}_2, \dots, \hat{a}_{k-1}]^T$ is of high accuracy. Assume $\hat{\mathbf{a}}_1^{k-1}$ to be correct and then Eq. (4.3) becomes

$$\hat{a}_k = \arg \max_{\tilde{\mathbf{a}}_k^{k+L_o-1} : \tilde{a}_k} \Pr(\mathbf{r}_k^{k+L_o-1} \mid \tilde{\mathbf{a}}_k^{k+L_o-1}, \hat{\mathbf{a}}_1^{k-1}, \hat{\mathbf{h}}_k^{k+L_o-1}) \quad (4.4)$$

Although the length of the possible sequence is shortened, the complexity of direct evaluation of Eq. (4.4) is still high. A truncated VA is thus resorted for efficient implementation. To make decision on a_k , the smallest state metric $\Gamma(s_{k+L_o-1})$ at time $(k + L_o - 1)$

needs to be found. In VA, the evaluation of $\Gamma(s_{k+L_o-1})$ can be splitted into two parts: one is the state metric at time $(k-1)$, the other one is the survivor branch increment from the k^{th} to the $(k+L_o-1)^{th}$ instant.

$$\Gamma(s_{k+L_o-1}) = \Gamma(s_{k-1}) - \log \left(\Pr \left(\mathbf{r}_k^{k+L_o-1} \mid \tilde{\mathbf{a}}_k^{k+L_o-1}, \hat{\mathbf{h}}_k^{k+L_o-1} \right) \right) \quad (4.5)$$

Let $s_{k-1}(\mathbf{a}_1^{k-1})$ denote the end state of the information sequence $\mathbf{a}_1^{k-1}$. As the previously detected sequence $\hat{\mathbf{a}}_1^{k-1}$ is assumed to be correct, the state metric which corresponds to the end state of $\hat{\mathbf{a}}_1^{k-1}$ is assigned 0, and for the other states at time $(k-1)$, large values are assigned. In other words, we have that

$$\Gamma(s_{k-1}) = \begin{cases} 0 & s_{k-1} = s_{k-1}(\hat{\mathbf{a}}_1^{k-1}) \\ \text{Inf} & \text{otherwise} \end{cases} \quad (4.6)$$

For determining $\Pr \left(\mathbf{r}_k^{k+L_o-1} \mid \tilde{\mathbf{a}}_k^{k+L_o-1}, \hat{\mathbf{h}}_k^{k+L_o-1} \right)$ in Eq. (4.5), $\hat{\mathbf{h}}_k^{k+L_o-1}$ is required to be known. A multi-step ahead Kalman prediction $\hat{\mathbf{h}}_k^{k+L_o-1} = [h_{k|k-1}, h_{k+1|k-1}, \dots, h_{k+L_o-1|k-1}]^T$ is used for its evaluation, where $h_{v|m}$ is the predicted channel coefficient at the v^{th} symbol time by the estimate at the m^{th} symbol time. Detailed description on the multi-step prediction will be introduced in Section 4.2.2. Given a known $\hat{\mathbf{h}}_k^{k+L_o-1}$, Eq. (4.5) can be solved using the VA in which the evaluation of state metrics starts from the k^{th} symbol and ends at the $(k+L_o-1)^{th}$ symbol. The survivor branch of each state is the branch with the smallest cumulative weight. The state metric is updated using the weight of the corresponding survivor branch. For $n = k, k+1, \dots, k+L_o-1$, we have that

$$\Gamma(s_n) = \arg \min_{s_{n-1} \in S_{n-1}(s_n)} (\Gamma(s_{n-1}) + \lambda(s_{n-1}, s_n)) \quad (4.7)$$

where $S_{n-1}(s_n)$ represents the set of states s_{n-1} in which there exist branches connecting state s_{n-1} to s_n . As the channel coefficients during the observation interval are obtained from Kalman prediction, we have

$$\lambda(s_{n-1}, s_n) = |r_n - h_{n|k-1} x(s_{n-1}, s_n)|^2 \quad (4.8)$$

where $|\cdot|$ denotes the Euclidean norm and $x(s_{n-1}, s_n)$ denotes the CPM signal connecting state s_{n-1} and s_n . Substituting Eqs. (4.6) and (4.8) into Eq. (4.7), $\Gamma(s_{k+L_o-1})$ can be obtained. Let $\hat{\mathbf{a}}_k^{k+L_o-1}(s_{k+L_o-1})$ denote the information sequence corresponding to the survivor path associated with the state s_{k+L_o-1} . We trace back from the state with the smallest state metric at time $(k+L_o-1)$ along its survivor branch until time k . A decision is made on a_k which causes the branch transition from time $(k-1)$ to time k . In other words, $\hat{a}_k$ is selected as the first element of sequence $\hat{\mathbf{a}}_k^{k+L_o-1} \left(\arg \min_{s_{k+L_o-1} \in S_{k+L_o-1}} \Gamma(s_{k+L_o-1}) \right)$.

4.2.2 Decision Directed Kalman Filter

We have shown previously that, for the k^{th} symbol decision, channel information $\hat{\mathbf{h}}_k^{k+L_o-1}$ is required to be known. Based on the AR model of the Rayleigh channel described in Section 2.2, the state equation in Eq. (2.13) can be iterated for L_o successive time intervals. The i^{th} channel prediction over the given observation interval can be obtained as

$$\mathbf{h}_{k+i|k-1} = \mathbf{F}^{i+1} \mathbf{h}_{k-1|k-1} + \sum_{n=0}^i \mathbf{F}^{i-n} \mathbf{w}_{k+n} \quad (4.9)$$

where $\mathbf{h}_{k+i|k-1} = [h_{k+i|k-1}, h_{k+i-1|k-1}, \dots, h_{k+i-N+1|k-1}]^T$, $0 \leq i \leq L_o - 1$. As a result, $\hat{\mathbf{h}}_k^{k+L_o-1} = [h_{k|k-1}, h_{k+1|k-1}, \dots, h_{k+L_o-1|k-1}]^T$. The second term of Eq. (4.9) is the prediction error and the corresponding error covariance can be expressed as

$$\mathbf{P}_{k+i|k-1} = \mathbf{F}^{i+1} \mathbf{P}_{k-1|k-1} (\mathbf{F}^{i+1})^H + \sum_{n=0}^i \mathbf{F}^{i-n} \mathbf{Q}_w (\mathbf{F}^{i-n})^H \quad (4.10)$$

After $\hat{\mathbf{h}}_k^{k+L_o-1}$ is obtained, $\hat{a}_k$ can be estimated via the aforementioned truncated VA algorithm. The estimated $\hat{a}_k$ is then used for channel updating at the k^{th} time. The CPM signal transmitted during the k^{th} symbol time can be uniquely determined by the detected symbol sequence $\hat{\mathbf{a}}_1^k$. Define a $1 \times N$ vector $\hat{\mathbf{x}}_k = [\hat{x}_k, 0, \dots, 0]$ where $\hat{x}_k$ is denoted as the regenerated CPM signal during the k^{th} symbol time, the KF updating equations can be

represented as given by [24]

$$\mathbf{K}_k = \mathbf{P}_{k|k-1} \hat{\mathbf{x}}_k^T (\sigma^2 + \hat{\mathbf{x}}_k \mathbf{P}_{k|k-1} \hat{\mathbf{x}}_k^T)^{-1} \quad (4.11)$$

$$\mathbf{h}_{k|k} = \mathbf{h}_{k|k-1} + \mathbf{K}_k (r_k - \hat{\mathbf{x}}_k \mathbf{h}_{k|k-1}) \quad (4.12)$$

$$\mathbf{P}_{k|k} = (\mathbf{I} - \mathbf{K}_k \hat{\mathbf{x}}_k) \mathbf{P}_{k|k-1} \quad (4.13)$$

where $\mathbf{K}_k$ is the Kalman gain at the k^{th} symbol time. For the detection of symbol a_{k+1} , the detected $\hat{a}_k$ is substituted in Eq. (4.6) for updating the state metric $\Gamma(s_k)$ and a prediction based on $\mathbf{h}_{k|k}$ is followed by a trellis search. These steps are iterated until the end of the received sequence.

4.2.3 Selection of the Observation Interval

The length of the observation interval L_o in Eq. (4.3) is an important parameter in the proposed scheme. If the channel information is known, the performance can be improved by increasing the value of L_o . However, in the proposed algorithm, longer observation interval will cause a larger channel prediction error. Therefore, there exists a tradeoff which requires L_o to be suitably determined. It is noted that the pair-wise error probability $P_e(i)$ with which the data bearing signal $x_i(t)$ is detected in error, under the MLSE criteria, has an upper bound given by [67, 68]

$$P_e(i) \leq \sum_{k \neq i} Q(|x_i(t) - x_k(t)|^2 E_b / N_0) \quad (4.14)$$

where $Q(\cdot)$ is the ‘Q’ function and $|\cdot|$ is the norm operation. When E_b/N_0 is reasonably high, it can be shown that the minimum distance $d_{\min} \triangleq \min_{i \neq k} \int (x_i(t) - x_k(t))^2 dt$ will dominate the detection error probability [85]. Let d_B represent the upper bound of $d_{\min}$. The bound would be attained if the observation interval is sufficiently long. At the receiver end, it is important to know the length of the observation interval required to achieve d_B ; let this observation interval be N_B . The minimum distance for some commonly used CPM

schemes are listed below. MSK achieves d_B when $N_B = 2$. The optimal modulation index for 1REC CPM is $h = 0.715$ which gives $d_B = 2.43$ when $N_B = 3$. For 2RC with $h = 0.5$, N_B is required to be 3 to attain $d_B = 2$ (which is equal to MSK). A method for the evaluation of d_B , $d_{\min}$ and N_B can be found in [69]. Since d_B is reached when $L_o = N_B$, further increase on L_o will not only increase the computational burden, but will also degrade the performance when the channel estimates are not accurate enough; for this reason an observation interval equal to or less than N_B is preferred.

4.3 Error Analysis

It is difficult to derive an exact BER for the proposed scheme because the data detection and channel estimation are coupled together. To simplify the analysis, it is assumed that there is no error in data decision feedback and only the effect of channel estimation error is considered. Thus, the analysis here provides an approximation for BER as described below.

4.3.1 Approximation for Bit Error Rate using only Channel Estimation Errors

It has been shown in [69] that, for AWGN channels, the BER of ML demodulation of CPM signals can be derived by considering the minimum distance event only, and is given by [69]

$$P_e \approx Q(\sqrt{d_{\min}^2 E_b / N_0}). \quad (4.15)$$

Eq. (4.15) will be used in the following derivation of an approximation of BER in Rayleigh flat fading channels. Note that data detection uses the predicted channel $h_{k|k-1}$ which has an irreducible error given by

$$\Delta h_k = h_k - h_{k|k-1}. \quad (4.16)$$

Substituting Eq. (4.16) into Eq. (2.19), we get

$$r_k = h_{k|k-1} x_k + \Delta h_k x_k + v_k. \quad (4.17)$$

The summation of the last two terms in Eq. (4.17) result in an equivalent noise component.

In the proposed demodulator, a DD KF is used for channel estimation. Under the assumption that the decision feedback is correct, the channel would obey $h_k \sim N(h_{k|k-1}, p_{k|k-1})$ where $N(e, p)$ denotes a Gaussian distribution with mean value of e and variance p . $p_{k|k-1}$ is the first element of $\mathbf{P}_{k|k-1}$ and it has different values at different kT . When the tracking length is sufficiently long, there exists a steady state channel prediction error covariance and we denote it as $\bar{p}$. Therefore, Δh_k would obey $\Delta h_k \sim N(0, \bar{p})$. Since Δh_k and v_k are uncorrelated Gaussian distributions, the equivalent noise component $\Delta h_k x_k + v_k$ is also Gaussian distributed. To simplify the presentation, the subscripts k is dropped and denote $\hat{h} = h_{k|k-1}$ in the following. Now the instantaneous received signal to noise ratio becomes

$$SNR = \frac{|\hat{h}|^2 E_b}{\bar{p} E_b + N_0} = \frac{|\hat{h}|^2 E_b / N_0}{\bar{p} E_b / N_0 + 1}. \quad (4.18)$$

Therefore, the bit error probability for a given channel prediction $\hat{h}$ becomes

$$P_{e|\hat{h}} \approx Q \left(\sqrt{d_{\min}^2 \frac{|\hat{h}|^2 E_b / N_0}{\bar{p} E_b / N_0 + 1}} \right). \quad (4.19)$$

Define $\eta \triangleq |\hat{h}|^2 \frac{E_b / N_0}{\bar{p} E_b / N_0 + 1}$, the above equation becomes $P_{e|\eta} \approx Q \left(\sqrt{d_{\min}^2 \eta} \right)$. Since the real channel h and the channel prediction error Δh are independently Gaussian distributed and are given by $h \sim N(0, 1)$ and $\Delta h \sim N(0, \bar{p})$, the predicted channel will obey $\hat{h} \sim N(0, \bar{p} + 1)$. Therefore, $|\hat{h}|$ is Rayleigh distributed and its pdf can be expressed as

$$p(|\hat{h}|) = \frac{2|\hat{h}|}{1 + \bar{p}} e^{-\left(\frac{|\hat{h}|^2}{1 + \bar{p}}\right)}. \quad (4.20)$$

Since $|\hat{h}|$ is Rayleigh distributed, $|\hat{h}|^2$ would be chi-square distributed. Using this it is easy to show that the pdf of η is given by

$$p(\eta) = \frac{(\bar{p}E_b/N_0 + 1)}{(1 + \bar{p})E_b/N_0} e^{-\frac{\eta(\bar{p}E_b/N_0 + 1)}{(1 + \bar{p})E_b/N_0}}. \quad (4.21)$$

To derive the error probability over all possible η , one must evaluate the conditional probability density function $P_{e|\eta}$ over the pdf of η to get

$$P_e \approx \int_0^\infty Q(\sqrt{d_{\min}^2 \eta}) p(\eta) d\eta. \quad (4.22)$$

After some manipulations, an approximation for the proposed demodulator is obtained as

$$P_e \approx \frac{1}{2} - \frac{d_{\min}}{2} \sqrt{\frac{(1 + \bar{p})E_b/N_0}{(1 + \bar{p})d_{\min}^2 E_b/N_0 + 2\bar{p}E_b/N_0 + 2}}. \quad (4.23)$$

Note that the error covariance $\bar{p}$ in above depends on the method used for channel estimation. The approximation BER when the channel is known can be obtained by setting $\bar{p} = 0$.

4.3.2 Channel Estimation Error Covariance

As noted, the average BER depends on the particular channel estimation technique used. In the proposed demodulator, a decision directed KF is used for channel estimation. Data detection of $\hat{a}_k$ is operated under the predicted channel $h_{k|k-1}$ and the corresponding predicted channel error covariance matrix is given by $\mathbf{P}_{k|k-1}$. At the steady state, $\mathbf{P}_{k|k-1}$ converge to $\mathbf{P}_\infty^-$, which satisfy the Riccati equation:

$$\mathbf{P}_\infty^- = \mathbf{F} \left(\mathbf{P}_\infty^- - \mathbf{P}_\infty^- \hat{\mathbf{x}}_k^T (\sigma^2 + \hat{\mathbf{x}}_k \mathbf{P}_\infty^- \hat{\mathbf{x}}_k^T)^{-1} \hat{\mathbf{x}}_k \mathbf{P}_\infty^- \right) \mathbf{F}^T + \mathbf{Q}_w. \quad (4.24)$$

Taking $\bar{p}$ as the first element of $\mathbf{P}_\infty^-$ and substituting into Eq. (4.23), the approximation of BER of the proposed demodulator is obtained. As Eq. (4.24) shows, the channel prediction error covariance relates to $\mathbf{F}$, $\mathbf{Q}_w$ and σ^2 . $\mathbf{F}$ and $\mathbf{Q}_w$ depends on the fading rate

Figure 4.2: Lower bound of MSE of channel estimation for the proposed algorithm

and the selection of prediction order. Subsequently, the fading rate, prediction order and the environmental noise affect the average BER. The steady state channel estimates error covariance matrix (denoted as $\mathbf{P}_\infty$) can also be related to the predicted channel error covariance $\mathbf{P}_\infty^-$ through

$$\mathbf{P}_\infty = \mathbf{P}_\infty^- - \mathbf{P}_\infty^- \hat{\mathbf{x}}_k^T (\sigma^2 + \hat{\mathbf{x}}_k^T \mathbf{P}_\infty^- \hat{\mathbf{x}}_k)^{-1} \hat{\mathbf{x}}_k \mathbf{P}_\infty^- \quad (4.25)$$

Eq. (4.25) is under the assumption that all feedback decisions are correct and the channel tracking reaches steady state. Thus $\mathbf{P}_\infty$ can be used to obtain a lower bound for channel estimation error.

4.3.3 A Numerical Example

We illustrate the error analysis through an example considering an MSK signal. In this example, a frame contains 30 symbols, of which 3 are pilot symbols. The order of the AR

Figure 4.3: Approximated BER for the proposed algorithm

model is 2 and the fading rate is 0.01. The MSE for channel estimation and the BER curves are shown in Fig. 4.2 and 4.3, respectively. As can be seen, the simulated MSE is worse than the derived MSE, which is obtained by solving the Riccati equation under different noise variance and subsequently using Eq. (4.25) to calculate P_∞ . It may serve as a lower bound of MSE. The difference may suggest that the channel estimation does not stay at steady state for enough long time. This difference, possibly together with other factors, may contribute to the difference between the approximated BER curve and the curve of simulation results in Fig. 4.3. Therefore, the derived BER curve can roughly give a trend of the performance of the proposed algorithms. However, it may not be accurate enough. This may be due to the various simplifications and assumptions made in the derivation, which may not hold in real and complicated environments.

Figure 4.4: BER performance of the proposed scheme for a full response CPM format

4.4 Simulation Results

Extensive simulations of CPM signals transmitted over a time-varying flat fading channel are performed to analyze the performance of the proposed algorithm. The selection of parameters, including the observation interval, the prediction order and the frame length, is discussed. The performance is compared with those of the PSP and SEP algorithms.

4.4.1 Performance of the Proposed Scheme with Different Fading Rates

Two types of CPM signals are used for simulation here: one is MSK; another is partial response CPM with a raised cosine frequency response over two symbol intervals. A frame contains 30 symbols, of which 3 are pilot symbols. The sampling rate is eight samples per symbol and the order of AR model for prediction is $N = 2$. The BER performance of the proposed demodulator in Section 4.2 with different normalized fading rate $f_d T$ is presented in Fig. 4.4 and Fig. 4.5. The values of $f_d T$, 0.001, 0.01, 0.05, are selected to represent

Figure 4.5: BER performance of the proposed scheme for a partial response CPM format

slow, moderate and fast fading channels, respectively. The performance of the VA endowed with the perfect channel state information (annotated as ‘Known Channel’) is also plotted in this figure for comparison. As can be seen, BER will increase as $f_d T$ increases, but the performance is still acceptable even when $f_d T$ is as high as 0.05.

4.4.2 Effect of Observation Interval, Prediction Order and Frame Length

The influence of the duration of the observation interval on BER performance is illustrated in Fig. 4.6 and Fig. 4.7 for fading rates 0.01 and 0.05, respectively. In each case, three E_b/N_0 values are considered. For illustration, only an MSK signal is considered. For a coherent receiver with known channel information, the performance will approach the optimum when $L_o \geq N_B$ [67]. For the MSK signal, $L_o = 2$ is sufficient for optimum demodulation. When channel is unknown and estimated at the receiver, an estimation error is inevitable. The error performance is firstly improved as the observation interval increases.

Figure 4.6: BER performance as a function of observation interval under $f_d T = 0.01$ with $E_b/N_0=10\text{dB}$, 20dB and 30dB .

Figure 4.7: BER performance as a function of observation interval under $f_d T = 0.05$ with $E_b/N_0=10\text{dB}$, 20dB and 30dB .

Figure 4.8: BER performance as a function of prediction order under $f_d T = 0.01$ with $E_b/N_0 = 10\text{dB}$, 20dB and 30dB .

According to Eq. (4.10), the prediction error $\mathbf{P}_{k+i|k-1}$ increases with the prediction step i . Therefore for a larger observation interval, performance is expected to degrade. As shown in Fig. 4.6 and 4.7, the performance loss caused by selecting $L_o > N_B$ is more severe when channel fading rate is high. It is also seen that, for different $f_d T$ and E_b/N_0 , the lowest BERs are all obtained when $L_o = N_B$, which validates the proposed selection.

The effect of the prediction order on the BER performance is shown in Fig. 4.8 and Fig. 4.9 for the normalized fading rates $f_d T = 0.01$ and $f_d T = 0.05$, respectively. In each case, three E_b/N_0 values are considered. Since the error covariance of Kalman prediction decreases along with the increase of prediction order, the BER performance is initially improved with increasing prediction order. However, when the prediction order exceeds certain value, the performance degrades. The reason is the following. The initialization of Kalman tracking is obtained by pilots and it has irreducible error variance. A large prediction order corresponds to a low prediction error covariance, which makes the Kalman

Figure 4.9: BER performance as a function of prediction order under $f_d T = 0.05$ with $E_b/N_0 = 10\text{dB}$, 20dB and 30dB .

tracking only relies on the prediction value and the information from recent observations are not utilized. It is also seen in Fig. 4.8 and Fig. 4.9 that, a larger prediction order is required for $f_d T = 0.05$ than $f_d T = 0.01$.

The effect of the frame length on channel estimation is investigated in Fig. 4.10 for $f_d T = 0.01$. Three different values of E_b/N_0 are used in the simulation. As seen in Fig. 4.10, a low mean square error of channel estimation is obtained when frame length is in a middle range. If the frame length is too small, the channel tracking may not converge at the end of each frame. If the frame length is too large, the performance will degrade due to a low insertion rate of pilot symbols. It is also observed that this middle region varies with E_b/N_0 . When E_b/N_0 is large (30dB in Fig. 4.10), this middle range would be quite wide which therefore allows a lower pilot symbol insertion rate. This is because the chance for track divergence in such environment is lower than in a low E_b/N_0 environment.

Figure 4.10: MSE of channel estimation versus frame length for $f_d T = 0.01$ ($E_b/N_0=10\text{dB}$, 20dB and 30dB).

4.4.3 Comparison between Different Reception Techniques

The proposed demodulator is compared with other algorithms in terms of BER performance. In the simulation, a frame contains 50 symbols and the first 2 symbols are pilots. The fading rate $f_d T = 0.01$, AR model order $N = 2$ and the observation interval of two symbol periods are adopted. Fig. 4.11 depicts the performances curves of four algorithms: the noncoherent block detection [19] (in which channel state information and cumulative phase are unnecessary for recovery), the SEP algorithm with a decision delay of 2, the PSP algorithm and the proposed algorithm. The performance curve with known channel information is also included for comparison. As can be seen, the proposed algorithm provides improved performance. For example, it provides a 2.5dB gain over the PSP algorithm and 3dB gain over the SEP algorithm when $BER = 10^{-3}$. Apart from the performance, the computation complexity is also an important aspect of an algorithm. For the three algo-

Figure 4.11: BER performance provided by the PSP algorithm, the SEP algorithm, the noncoherent block detection and the proposed algorithm.

gorithms, the complexity is mainly contributed by the branch metric evaluation in the VA. For SEP and PSP algorithms, the computational complexity per symbol is $O(pM^L)$, while it is $O(L_o pM^L)$ for the proposed algorithm. L_o is usually a small integer for common CPM signals, e.g., $L_o = 2$ for MSK signal and $L_o = 3$ for partial response CPM signal with a raised cosine frequency response over two symbol intervals. Therefore, the complexity of the proposed algorithm increases slightly while having a relatively large performance gain.

4.4.4 Advantage of MSK over BPSK in the Proposed Decision-directed Channel Tracking

The advantages offered by MSK over BPSK on error propagation elimination in using the DD approach is illustrated in Figs. 4.12 and 4.13. MSK provides the same error performance as of BPSK over an AWGN channel. Here, it is shown that in an unknown fading channel, when data detection and channel estimation are based on the DD approach, the

Figure 4.12: Error indicator for MSK and BPSK in the proposed joint data and channel estimation scheme.

Figure 4.13: BER performance comparison among BPSK and MSK.

performances of these two modulation schemes are not similar. In the proposed joint data detection and channel estimator for the MSK scheme, a replica of the transmitted signal is regenerated at the receiver by using the hard decision feedback. For every two errors, the regenerated transmitted MSK signal will be restored to its correct value. The nature of the error propagation phenomenon is illustrated in Fig. 4.12. Simulations are performed over a flat fading channel with $f_d T = 0.01$ and $E_b/N_0 = 15$ dB for MSK and BPSK, respectively. One pilot symbol is inserted every 30 symbols for the initialization of tracking parameters. The channel amplitude and the corresponding error indicator are shown in this figure. A pulse generated by the error indicator indicates an error at the receiver for a given bit. The errors for a BPSK signal, in some cases shown in the figure, propagate until the appearance of the pilot symbol of the next frame. Due to the self-correction property of decision feedback CPM, the errors fade away after several symbols.

Fig. 4.13 shows the BER performance of MSK and BPSK for a normalized fading rate $f_d T = 0.01$ under different frame lengths. Three pilots are inserted in every frame. The performances of MSK and BPSK are very similar when the frame length is 30. However, when the frame length is 300, an obvious performance improvement is obtained if BPSK is replaced by MSK. Because of the error propagation caused by inaccurate data detection with BPSK in a DD approach, it is necessary to insert pilot symbols more frequently to prevent the divergence of Kalman tracking. However, this problem is not so severe in MSK due to its self error-correcting ability. The performances provided by MSK with a pilot spacing of 30 and 300 symbols are very similar. However, the performances with these two pilot spacings are quite different for BPSK. Fig. 4.13 evidences that the performance of MSK with a DD approach does not depend heavily on the pilot spacing and hence MSK provides a higher bandwidth efficiency than BPSK.

4.5 Summary

In this chapter we had addressed the problem of joint data detection and channel estimation for uncoded CPM signals transmitted over a time-varying flat fading channel. A multi-step forward channel prediction over a given observation interval is obtained via Kalman prediction. Then a decision is taken on the first symbol of the observation interval in a truncated VA. Finally the detected symbol is used for channel updating and state updating for the detection of the next symbol. These steps are iterated up until the end of the received sequence. The prediction over a given observation interval guarantees zero decision delay and at the same time maintains the accuracy of the survivor path selection. Therefore, the proposed method is expected to achieve a better performance than the PSP and SEP methods and simulation results confirm the expectation. Error analysis of the proposed algorithm and the impact of the selection of various design parameters had also been investigated.

Chapter 5

Joint Data Detection and Channel Estimation for Serially Concatenated CPM over Frequency-Flat Fading Channels

In Chapter 4 the problem of joint data detection and channel estimation for uncoded CPM signals has been addressed. It has been shown that when the fading rate is fast, reliable channel tracking is difficult and thus the accuracy of data detection would not be satisfactory. Moreover, even with perfect knowledge of channel information, data transmission at low E_b/N_0 value may not satisfy the BER requirements of certain communication systems. Therefore, channel coding is introduced to protect data against errors. In Chapter 4, only hard decision outputs have been considered; however this is not suitable in the case of iterative receivers which need SISO detectors. Thus, in this chapter, we extend the hard output demodulator developed in Chapter 4 to a novel adaptive SISO demodulator for SC-CPM signals transmitted over a frequency flat fading channel. Unlike conventional SISO algorithms in which the number of states increases exponentially and linear prediction for channel estimation is used, the proposed method estimates the channel without an increase in the number of the trellis states. The proposed SISO demodulator consists of two main parts: a symbol by symbol MAP demodulator and a channel tracker. These two parts ex-

change and update information in every symbol interval. Due to the inherent memory in CPM, demodulation usually needs a large latency which degrades channel tracking capability. To solve this problem, we propose an algorithm using a multi-step channel prediction and the corresponding prediction error covariance for data detection. Then the estimated data is used for Kalman updating. Due to its ability of incorporating the a priori symbol probabilities and outputting soft decisions, the proposed SISO demodulator is well suited for SCCPM systems, which allows iterative processing. Both the convergence behavior and BER results are illustrated for the proposed iterative receiver.

5.1 Introduction

A joint demodulation and decoding scheme, which combines the entire memory of both the demodulator and the decoder, can provide the optimum performance for SCCPM signals. However, the considerable complexity of the super trellis makes it difficult to adopt in real applications. On the other hand, if the demodulator and the decoder are separated, the performance is expected to be far from the optimum. Fortunately, an iterative receiver which exchanges information between the demodulator and the decoder can iteratively achieve near optimum performance with a moderate complexity. In the literature, the design guideline for the encoder and the interleaver for serially concatenated SCCPM signals with iterative detection has been analyzed in [42]. The problem of iterative detection when channel state information is perfectly known at the receiver has been addressed in [44]. Several pioneer works on SCCPM signals appear in [1, 3, 46, 47].

Note that the proposed hard output demodulator of Chapter 4 as well as the PSP and SEP algorithms can only produce hard decisions which are not suitable for an iterative receiver where soft information is needed for subsequent processing. Therefore, a family of adaptive SISO algorithms based on the PSP and SEP algorithms have been proposed in [46, 86], which are denoted as PSP based SISO and SEP based SISO, respectively. It has

Figure 5.1: Block diagram of transmitter and iterative receiver for SCCPM systems

been proven in [86] that the PSP based SISO algorithm is better than the SEP based SISO when channel variation is considerable. The PSP based SISO consists of two categories, the SISO forward only (SISO-FO) and SISO forward backward (SISO-FB) algorithms. In [2], it has been shown that the PSP based SISO-FO algorithm performs better than the SISO-FB algorithm for CPM signals. Another SISO demodulator has been addressed in [87] where the expectation maximization (EM) algorithm is used to estimate the channel. The EM algorithm performs quite well in quasi-static channels but its iterative nature for refining one parameter by multiple observations makes it difficult to be applied for time varying channels [88]. Motivated by the performance improvement brought by SISO demodulators as analyzed above, the proposed hard output demodulator in Chapter 4 is then extended to a SISO demodulator for SCCPM signals over an unknown time varying flat fading channel.

5.2 System Model

The block diagram of the transmitter and the receiver of a SCCPM system is depicted in Fig. 5.1 [89]. The information bit sequence I_k is first encoded by a convolutional encoder. The coded bit sequence c_k is sent to a random interleaver. The CPM modulator takes the interleaved bit sequence a_k and pilots symbols (for channel initialization) as its input and

outputs the modulated signal x_k . The modulated signal is then transmitted over a rayleigh flat fading channel h_k , which causes a multiplicative distortion to the transmitted signal. The detailed description of CPM signal x_k and the flat fading channel h_k (which can be modeled as a Markov process) was presented in Chapter 2. In iterative processing, soft information from the demodulator is passed to the decoder. Compared with the delivery of conventional hard information, delivery of soft information causes a smaller information loss. However, even if accurate soft information is passed to the decoder, the overall system performance is still far away from the optimal one especially in fading channels. This motivates iterative processing in which earlier stages utilize soft information from the later stages [90]. In Fig. 5.1, the proposed SISO demodulator acts as not only a CPM demodulator but also as a channel estimator. Its ability of incorporating the a priori symbol probability and outputting soft information makes it suitable for iterative processing. In each iteration, the SISO demodulator takes the soft information $L_a(a_k)$ provided by the decoder from the previous iteration as its a priori probability to perform joint data detection and channel estimation. The output of SISO demodulator is the log likelihood ratio (LLR) of coded bits a_k , denoted as $L(a_k)$. The LLR which is related to both the a priori probabilities and the a posteriori probabilities is given by [91]

$$\begin{aligned} L(a_k) &= \log \frac{\Pr(a_k=1|r_k)}{\Pr(a_k=-1|r_k)} \\ &= \log \frac{\Pr(r_k|a_k=1)}{\Pr(r_k|a_k=-1)} + \log \frac{\Pr(a_k=1)}{\Pr(a_k=-1)} = L_e(a_k) + L_a(a_k) \end{aligned} \quad (5.1)$$

where $L_e(a_k)$ is the extrinsic information. Note that during iterative processing, the a priori information passed to one stage cannot include the information originated from the same stage during the previous iteration [3]. To achieve this, the output LLRs of the SISO demodulator must subtract their input a priori LLRs $L_a(a_k)$ before they are delivered to the next stage [92]. Therefore, we have $L_e(a_k) = L(a_k) - L_a(a_k)$. These extrinsic LLRs $L_e(a_k)$ are then deinterleaved to obtain the LLRs of c_k , which are denoted as $L_a(c_k)$. As the considered channel coefficients are not independent between adjacent symbols, errors typically occur in bursts when the channel experiences a deep fade. The interleaver is essential

to break these continuous errors into non-continuous pattern and so that the subsequent decoder is able to correct these errors. At the end a SISO decoder employing the BCJR algorithm outputs the estimated information symbol $\hat{I}_k$ and the LLRs of the coded sequence $L(c_k)$. Before passing to the next stage, $L_e(c_k) = L(c_k) - L_a(c_k)$ is evaluated and $L_e(c_k)$ is interleaved to provide the updated priori probability for the SISO demodulator in the next iteration [93]. By exchanging the soft information between the SISO demodulator and the SISO convolutional decoder, data detection is expected to be more accurate. Furthermore, the error covariance of the channel estimation, obtained by the proposed DD KF approach, is expected to decrease through iterations due to the increased accuracy of detected data. Therefore, the performance of the whole system is improved.

5.3 The Proposed SISO demodulator

In this section, a novel SISO demodulator is proposed which overcomes the mentioned shortcomings of the PSP-based SISO and the SEP-based SISO algorithms. The proposed SISO iterative demodulator consists of two main parts: a truncated BCJR algorithm and a DD Kalman filtering. A convergence analysis for the proposed iterative receiver is also presented.

5.3.1 Optimal MAP Symbol Detection

Block transmission is assumed in order to make the modulated signals independent among blocks. Therefore we operate the system in such a manner that the start state and the end state of the CPM signal in every block are the zero state. This can be accomplished by inserting known symbols at the end of each block to force the state return to the zero state. One way for calculating the symbols to be inserted can be found in [94].

Due to the correlated fading and symbol dependence introduced by CPM modulation, the symbol by symbol maximum a posteriori probability (MAP) detection of a_k in a block

$\mathbf{a}_1^{N_b}$ under known $\mathbf{h}_1^{N_b}$ is [95]

$$\hat{a}_k = \arg \max_{\tilde{a}_k \in \{\pm 1, \pm 3, \dots, \pm(M-1)\}} \Pr(\tilde{a}_k \mid \mathbf{r}_1^{N_b}, \mathbf{h}_1^{N_b}) \quad (5.2)$$

where $\hat{a}_k$ and $\tilde{a}_k$ are the estimate and hypothesis of a_k , respectively. When a hard output is needed, only symbol $a_k \in \{\pm 1, \pm 3, \dots, \pm(M-1)\}$ with the highest $\Pr(a_k)$ will be assigned to the detected symbol. If a soft output is required, $L(a_k)$ is delivered to the next step for further processing. Applying Bayes' rule and total probability, Eq. (5.2) becomes

$$\hat{a}_k = \arg \max_{\tilde{a}_k \in \{\pm 1, \pm 3, \dots, \pm(M-1)\}} \sum_{\tilde{\mathbf{a}}_1^{N_b} : \tilde{a}_k} \Pr(\mathbf{r}_1^{N_b} \mid \tilde{\mathbf{a}}_1^{N_b}, \mathbf{h}_1^{N_b}) \Pr(\tilde{\mathbf{a}}_1^{N_b}) \quad (5.3)$$

where $\tilde{\mathbf{a}}_1^{N_b} : \tilde{a}_k$ represents the set of all the possible symbol sequences characterized by the hypothesized symbol $\tilde{a}_k$. Direct evaluation of Eq. (5.3) has a prohibitively high complexity. The BCJR algorithm proposed in [7], which has been discussed in Section 2.3.2, is a computationally efficient method for solving this problem.

5.3.2 Truncated BCJR Algorithm and Kalman Filtering

Note that the symbol by symbol MAP detection of a_k in Eq. (5.3) is performed under known channel conditions. When the channel is unknown, this criterion becomes

$$\hat{a}_k = \arg \max_{\tilde{a}_k \in \{\pm 1, \pm 3, \dots, \pm(M-1)\}} \sum_{\tilde{\mathbf{a}}_1^{N_b} : \tilde{a}_k} \int \Pr(\mathbf{r}_1^{N_b} \mid \tilde{\mathbf{a}}_1^{N_b}, \mathbf{h}_1^{N_b}) \Pr(\tilde{\mathbf{a}}_1^{N_b}) f(\mathbf{h}_1^{N_b}) d\mathbf{h}_1^{N_b}, \quad (5.4)$$

where the unknown parameter $\mathbf{h}_1^{N_b}$ is considered as a realization of a random vector with the assigned probability density function (PDF) $f(\mathbf{h}_1^{N_b})$. However, the integration appearing in Eq.(5.4) can not be evaluated easily. Another way is to estimate the unknown parameter $\mathbf{h}_1^{N_b}$ and then use it to determine the probability of $\Pr(\mathbf{r}_1^{N_b} \mid \tilde{\mathbf{a}}_1^{N_b}, \hat{\mathbf{h}}_1^{N_b})$. Due to the difficulty of multidimensional integration in Eq. (5.4), we use the latter method in this chapter, so that the decision criterion becomes

$$\hat{a}_k = \arg \max_{\tilde{a}_k \in \{\pm 1, \pm 3, \dots, \pm(M-1)\}} \sum_{\tilde{\mathbf{a}}_1^{N_b} : \tilde{a}_k} \Pr(\mathbf{r}_1^{N_b} \mid \tilde{\mathbf{a}}_1^{N_b}, \hat{\mathbf{h}}_1^{N_b}) \Pr(\tilde{\mathbf{a}}_1^{N_b}), \quad (5.5)$$

where $\hat{\mathbf{h}}_1^{N_b}$ is the vector of estimated channel coefficients.

In Chapter 4, we proposed a method which outperforms two typically used DD algorithms for CPM (namely, the PSP and SEP method). The reason for the performance improvement lies in the fact that the proposed method solves the problem of the conflicting requirements on the length of decision delay when both the channel tracking ability and the accuracy of tentative decision have to be taken into account. However, the method proposed in Chapter 4, the PSP and the SEP algorithms can only produces hard outputs which are not suitable for iterative processing. The PSP and the SEP algorithms have been extended to a family of A-SISO algorithms which can incorporate the a priori probabilities and output soft decisions. In a SEP based A-SISO algorithms, only one channel estimate is retained per symbol period. In a PSP based A-SISO algorithm, instead, channel estimation is performed once for each state. The evaluations of the quantities α and β in the BCJR algorithm are carried out in the forward and in the backward directions, respectively. Therefore, channel estimation in PSP-SISO is characterized by two values per-state. If only the channel estimation from either the forward or backward recursion is used, the resulting method is denoted A-SISO forward only (A-SISO-FO) or A-SISO backward only (A-SISO-BO), respectively. If the channel estimates in both directions are binded to produce a new estimate, it is called A-SISO forward backward (A-SISO-FB). It has been shown in [86] that a PSP based A-SISO algorithm performs better than a SEP based A-SISO in the presence of considerable channel variations. Meanwhile, for PSP based A-SISO algorithms, the superiority of A-SISO-FO over A-SISO-FB counterpart has been shown in [1] for CPM signals. In this section, we extend the method proposed in Chapter 4 to a SISO demodulator.

Similar to the approximation method adopted in Section 4.2.1, Eq. (5.3) can be approximated as

$$\hat{a}_k = \arg \max_{\tilde{a}_k \in \{\pm 1, \pm 3, \dots, \pm(M-1)\}} \sum_{\tilde{\mathbf{a}}_k^{k+L_o-1}} \Pr(\mathbf{r}_k^{k+L_o-1} | \tilde{\mathbf{a}}_k^{k+L_o-1}, \hat{\mathbf{a}}_1^{k-1}, \hat{\mathbf{h}}_k^{k+L_o-1}) \Pr(\tilde{\mathbf{a}}_k^{k+L_o-1}) \quad (5.6)$$

Since the input of the CPM modulator is the output of the interleaver, the input symbols can be considered as independent such that

$$\Pr(\tilde{\mathbf{a}}_k^{k+L_o-1}) = \prod_{n=k}^{k+L_o-1} \Pr(a_n) \quad (5.7)$$

Followed by a recursive expansion, Eq. (5.6) becomes

$$\hat{a}_k = \arg \max_{\tilde{a}_k \in \{\pm 1, \pm 3, \dots, \pm(M-1)\}} \sum_{\tilde{\mathbf{a}}_k^{k+L_o-1}} \prod_{n=k}^{k+L_o-1} \Pr(r_n | \mathbf{r}_k^{n-1}, \tilde{\mathbf{a}}_k^n, \hat{\mathbf{a}}_1^{k-1}, \hat{\mathbf{h}}_k^n) \Pr(a_n) \quad (5.8)$$

For simplicity of presentation, only binary transmission with $M = 2$ is considered here.

When soft outputs are required for subsequent processing, $L(a_k)$ is evaluated as

$$L(a_k) = \frac{\sum_{\tilde{\mathbf{a}}_k^{k+L_o-1}, a_k=1} \prod_{n=k}^{k+L_o-1} \Pr(r_n | \mathbf{r}_k^{n-1}, \tilde{\mathbf{a}}_k^n, \hat{\mathbf{a}}_1^{k-1}, \hat{\mathbf{h}}_k^n) \Pr(a_n)}{\sum_{\tilde{\mathbf{a}}_k^{k+L_o-1}, a_k=-1} \prod_{n=k}^{k+L_o-1} \Pr(r_n | \mathbf{r}_k^{n-1}, \tilde{\mathbf{a}}_k^n, \hat{\mathbf{a}}_1^{k-1}, \hat{\mathbf{h}}_k^n) \Pr(a_n)} \quad (5.9)$$

Direct evaluation of Eq. (5.9) is prohibitively complex. Here a truncated BCJR algorithm is used for efficient implementation. Following [7], it can be shown that

$$L(a_k) = \frac{\sum_{ST_1^k} \gamma(s_k \rightarrow s_{k+1}) \alpha(s_k) \beta(s_{k+1}) \Pr(a_k = 1)}{\sum_{ST_{-1}^k} \gamma(s_k \rightarrow s_{k+1}) \alpha(s_k) \beta(s_{k+1}) \Pr(a_k = 0)} \quad (5.10)$$

where s_k is the state at k^{th} time, α , β are the forward and backward coefficients, ST_1^k and ST_{-1}^k are the branches connecting the state s_k to s_{k+1} associated with the input symbols 1 and -1 , respectively. For the k^{th} symbol detection, $L(a_k)$ is evaluated under a truncated interval which starts at the k^{th} symbol time and ends at $(k + L_o - 1)^{th}$ symbol time. As the data decision is made at the first symbol of the observation interval, only one initialization is necessary when considering the evaluation of the forward coefficients for every truncated interval. This initialization can be easily obtained by means of the previously decided symbols. Let $\hat{s}_k(\hat{\mathbf{a}}_1^{k-1})$ denote the state associated with the decided data sequence $\hat{\mathbf{a}}_1^{k-1}$. Based on the approximation of Eq. (5.8), we have $\alpha(s_k = \hat{s}_k(\hat{\mathbf{a}}_1^{k-1})) = 1$ and for other

states at the k^{th} symbol time, α will be equal to 0. The initialization $\beta(s_{k+L_o}) = 1$ is adopted for all possible states at the $(k + L_o)^{th}$ symbol time. The evaluation of α and β are based on γ . These two coefficients can be calculated recursively as [7]

$$\begin{aligned}\alpha(s_{k+1}) &= \sum_{s_n \in S} \gamma(s_k = s_n \rightarrow s_{k+1}) \alpha(s_k = s_n) \\ \beta(s_{k+1}) &= \sum_{s_n \in S} \gamma(s_k \rightarrow s_{k+1} = s_n) \beta(s_{k+1} = s_n)\end{aligned}\tag{5.11}$$

where S is the set of states at every symbol time.

As same as the hard output demodulator in Section 4.2, a multi-step Kalman prediction is used to evaluate the channel coefficients during the observation interval. Furthermore, the multi-step Kalman prediction can provide exact prediction error covariance $\mathbf{P}_{k|k-1}$, which can be used to obtain a more accurate $L(a_k)$. It has been shown in Eq. (4.17) that, when channel estimation error is considered, an equivalent noise component appears at the receiver, which is denoted as $m_k = \Delta h_k x_k + v_k$. Since Δh_k and v_k are independently Gaussian distributed, m_k is Gaussian and it obeys $m_k \sim N(0, p_{k|k-1})$, where $p_{k|k-1}$ is the first element of $\mathbf{P}_{k|k-1}$ in Eq. (4.10). We can thus modify the truncated BCJR algorithm incorporating the channel estimation error as follows

$$\gamma(s_k \rightarrow s_{k+1}) = \exp \left(\frac{1}{2\sigma^2 + p_{k|k-1}} |r_k - h_{k|k-1} x(s_k \rightarrow s_{k+1})|^2 \right)\tag{5.12}$$

where $x(s_k \rightarrow s_{k+1})$ denotes the CPM signal associated with the state transition from s_k to s_{k+1} . With the estimated γ , α and β , both the hard output $\hat{a}_k$ and soft output $L(a_k)$ can be easily obtained by Eq. (5.10). Soft output $L(a_k)$ is presented to the decoder for further processing and the hard decision $\hat{a}_k$ is fed back for two purposes: one is for establishing the initial state for the next symbol decision in the truncated BCJR procedure and the other is for regenerating the CPM signal during the k^{th} symbol time $\hat{x}_k$. Given a known $\hat{x}_k$, the KF updating equations given by Eqs. (4.11-4.13) can be used to evaluate $\mathbf{h}_{k|k}$. The soft information of the next symbol $L(a_{k+1})$ is then evaluated using the predicted channel and

the predicted channel error covariance. These steps are iterated until the end of the received sequence.

We summarize the proposed A-SISO demodulator in Algorithm 1.

Algorithm 1: Description of the proposed adaptive SISO demodulator

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1 Initialization:
2 for  $k = 1 : pilot$  do
3    $\lfloor$  obtain  $\mathbf{h}_{k|k}, \mathbf{P}_{k|k}$  from training
4 Recursion:
5 for  $k = (pilot + 1) : (N_b)$  do
6   1. Use Eq. (4.9) to obtain  $[h_{k|k-1}, h_{k+1|k-1}, \dots, h_{k+L_o-1|k-1}]$  and the
      corresponding error covariance matrix;
7   2. if APP of  $L_e(a_k)$  exists then
8      $\lfloor$   $\Pr(a_k)$  is assigned according to  $L_e(a_k)$ ;
9   else
10     $\lfloor$   $\Pr(a_k)$  is uniformly distributed
11   3. According to Eq. (5.10), output  $L(a_k)$ ;
12   4. Regenerate  $\hat{x}_k$  based on the tracked trellis state  $\hat{s}_k$  and the detected symbol  $\hat{a}_k$ ;
13   5. Update  $\mathbf{h}_{k|k}$  and the corresponding error covariance matrix;
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5.4 Convergence Analysis

In this section, the extrinsic information transfer (EXIT) chart is exploited to analyze the convergence behavior of the proposed iterative receiver. The EXIT chart, which uses mutual information (MI) to measure the input and output extrinsic information, was first proposed for the construction of turbo codes and then extended to the convergence analysis of iterative receivers. The MI between two variables x and y is defined as [96]

$$I(x; y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{x;y}(x, y) \log_2 \frac{f_{x|y}(x|y)}{f_x(x)} dx dy. \quad (5.13)$$

Let m , $L_a(m)$ and $L_e(m)$ denote the input symbol, the input a priori information and the extrinsic information at the output of the SISO demodulator, respectively. The MI

Figure 5.2: EXIT charts for MSK with different convolutional encoders (AWGN channel is considered).

between m and $L_a(m)$ is denoted as $I_a(m)$, while the MI between m and $L_e(m)$ is denoted as $I_e(m)$. The MI can be obtained in two ways, e.g., using a histogram-based approach or a parametric estimation method. A Histogram-based approach is adopted in this chapter since the parametric estimation method is based on an assumption of Gaussianity. The correspondence rule between I_a and I_e is called extrinsic information transfer function [97].

As shown in Fig. 5.2, the SISO demodulator and SISO convolutional decoder exchange information in each iteration and the corresponding EXIT chart consists of two curves. One curve is plotted for the SISO demodulator with MI of $I_{a,demodulator} = I(L_a(a_k), a_k)$ as the horizontal axis and the MI of $I_{e,demodulator} = I(L_e(a_k), a_k)$ as the vertical axis. The other one is plotted for the SISO decoder with MI $I_{a,decoder} = I(L_a(c_k), c_k)$ as the vertical axis and the MI $I_{e,decoder} = I(L_e(c_k), c_k)$ as the horizontal axis. Since the output LLR of the demodulator is the input of the decoder and the output LLR of the decoder is the input of

the demodulator in the next iteration, the convergence behavior can be observed by stepping between these two curves of the EXIT chart. A wide tunnel between the two curves is preferred since it indicates a rapid convergence. When the two curves intersect, the MI will converge to the crossover point [98]. For the SCCPM system shown in Fig. 5.2, the EXIT chart can be used to find the convergence E_b/N_0 thresholds for different combinations of modulation schemes and convolutional codes. Fig. 5.2 shows the EXIT chart for MSK signals with two convolutional codes over an AWGN channel; such codes have generator polynomials $[5, 7]_8$ and $[5, 7, 7]_8$ and their corresponding rates are $1/2$ and $1/3$. The transfer curve of demodulator also depends on the value of E_b/N_0 . When operating under a low value of E_b/N_0 , the extrinsic curve is lower. For a convolutional encoding scheme, since the decoder is independent of environmental noise and channel conditions, the corresponding extrinsic transfer curve is fixed for any channel condition. These results show that, for a fixed CPM scheme, different convolutional codes have different E_b/N_0 convergence thresholds. The convergence thresholds of the code $[5, 7]_8$ and $[5, 7, 7]_8$ are 0.9 dB and -1 dB, respectively. The extrinsic transfer function of the code $[5, 7, 7]_8$ is lower compared to $[5, 7]_8$, which indicates that, even at a E_b/N_0 of -1 dB, the iterative processing can still lead to convergence to a small BER at the cost of more iterations. However, the better performance of code $[5, 7, 7]_8$ over the code $[5, 7]_8$ is achieved at the price of a reduced bandwidth efficiency. Note also that a decoder for a code with a longer constraint length requires a higher computational complexity.

The EXIT charts in Fig. 5.2 refer to the behavior of the iterative receiver operating under an AWGN channel. We have also considered a SISO demodulator which performs joint data detection and channel estimation in the presence of a time-varying flat fading channels. According to Eqs. (5.10) and (5.12), the output LLRs $L(a_k)$ of the proposed SISO demodulator are evaluated using the estimated channel. Thus, the unavoidable channel estimation errors affect the extrinsic transfer function. From Eqs. (5.10) and (5.12),

it can be concluded that, under a specified data detection and channel estimation method, E_b/N_0 and the accuracy of channel estimates can quantify the output MI. Furthermore, the accuracy of channel estimates depends on E_b/N_0 and $f_d T$. Therefore the output MI of the proposed SISO demodulator can be characterized by

$$I_{e,\text{demodulator}} = G(I_{a,\text{demodulator}}, \frac{E_b}{N_0}, f_d T), \quad (5.14)$$

where $G(\cdot, \cdot, \cdot)$ refers to the correspondence relationship.

Figure 5.3: EXIT chart for the proposed iterative receiver for different values of E_b/N_0

Fig. 5.3 shows the effects of E_b/N_0 on the extrinsic transfer function of the proposed SISO demodulator at the fixed fading rate $f_d T = 0.01$. For the same value of E_b/N_0 , the transfer curves of the proposed demodulator are much lower than those evaluated for an AWGN channel. It is also interesting to note that, for an AWGN channel there exists a value of E_b/N_0 for which the demodulator-decoder trajectories just manage to sneak through a narrow tunnel [98]. Therefore, the BER found for that E_b/N_0 converges to a

Figure 5.4: EXIT chart for the proposed iterative receiver for different fading rates

very small value through iterations and a turbo cliff (which is an abrupt decrease in BER) around that E_b/N_0 can be found. However, in Fig. 5.3, such a bottleneck region is not seen. This implies that, for the proposed SISO demodulator, a turbo cliff can not be found in the BER curves. When $E_b/N_0 = 4$ dB, an intersection is observed at $I_{a, \text{demodulator}} = 0.5$. This indicates that, as iterations proceed, MI increases and eventually sticks at the intersection point. When E_b/N_0 is equal or larger than 8dB, the crossover point of the SISO demodulator curve and the SISO decoder curve is high. It means that the iterative processing can lead to convergence to a very small BER. Fig. 5.4 shows the effect of the channel fading rate $f_d T$ on the extrinsic transfer function of the proposed SISO demodulator for a fixed $E_b/N_0 = 10$ dB. As the fading rate increases, the transfer function of the demodulator decreases. The reason is that, a larger channel estimation error is expected for a higher $f_d T$, which causes the lowering of the transfer function.

Figure 5.5: BER performance provided by a demodulator with soft outputs and by one with hard outputs in a serially concatenated system.

5.5 Simulation Results

In this section, the effectiveness of the proposed SISO demodulator for SCCPM is evaluated. The selected convolutional encoder has a generator polynomial $[5, 7]_8$, constraint length of 3 and rate of $1/2$. A random interleaver is used and, for simplicity, MSK is adopted.

5.5.1 On the Effectiveness of Soft Information in Concatenated System

Firstly, the benefit of replacing hard decision by soft decision in serially concatenated systems is assessed. When soft decisions are considered, the output probabilities of the demodulator is fed to the decoder for further processing. If hard decisions are taken, the output data decisions (which belong to $\{\pm 1, \pm 3, \dots, \pm(M-1)\}$) are passed to the decoder. Iterations are not performed in generating the simulation results shown in Fig. 5.5. The

Figure 5.6: Effect of the interleaver size on the proposed iterative receiver

performances of hard decisions and soft decisions of the proposed algorithm are compared to each other with two fading rates: $f_d T = 0.01$ and 0.05 . Fig. 5.5 shows that if soft information is provided in place of hard information by the demodulator to the convolutional decoder, a significant performance improvement can be obtained. This is because soft decisions contain more information than hard decisions so providing more flexibility for further processing. Note also that detection using soft information is essential in all concatenated systems.

5.5.2 The Effects of Interleaver Size

In Fig. 5.6 the BER performance of the proposed receiver is shown against the number of iterations for different interleaver sizes ($N_t = 100, 640, 1600, 8000$ and 16000); the channel parameters are $f_d T = 0.01$ and $E_b/N_0 = 8$ dB. An interleaver is used to spread the occurrence of errors in a non-contiguous way. Besides the burst of errors caused by the fading

Figure 5.7: Effect of the interleaver size on the BER performance for different fading rates ($f_d T = 0.001$, $f_d T = 0.005$ and $f_d T = 0.01$).

channel, using the proposed algorithm in a DD manner makes the problem of error propagation more pronounced. Therefore, it is necessary to have an interleaver which makes the errors at the output of the demodulator independent of each other. As can be seen, when the interleaver size is small (e.g., $N_t = 100$), BER performance does not improve through iterations. As the interleaver size increases, BER performance begins to improve with iterations. Thus, we can conclude that a sufficiently large interleaver size is an important requirement for the iterative receiver to improve performance through iterations.

In general, increasing the interleave size is better, when considering the BER performance. However, large interleaver size causes a large processing delay, and a good choice of the interleaver size is the value above which the performance does not improve significantly. Fig. 5.7 shows the effect of the interleaver size for different fading rates. The BER curves are obtained after five iterations for $E_b/N_0 = 8$ dB. When the channel is slow time-varying (e.g., $f_d T = 0.001$), the optimum selection of interleaver size is $N_t = 16000$.

Figure 5.8: Effect of the interleaver size on the BER performance for different E_b/N_0 ($E_b/N_0 = 8\text{dB}$ and $E_b/N_0 = 10\text{dB}$).

When the fading rate is moderate (e.g., $f_d T = 0.005$, the optimum value of interleaver size becomes 8000. For a faster time-varying channel ($f_d T = 0.01$), when $N_t > 4000$, the performance improvement is only marginal. It can be concluded that the proposed iterative receiver with a slow time-varying channel needs a larger interleaver size than the one with a fast fading channel. The reason is the following. The duration of a deep fade is long when the channel is slow fading, causing a long error burst at the output of the proposed SISO demodulator. Therefore, a large interleaver size is required to make these errors occur in a non-contiguous manner. Fig. 5.8 shows the effect of interleaver size on BER performance for different E_b/N_0 under a fixed fading rate $f_d T = 0.01$, with the value of E_b/N_0 equals to 8dB and 10dB. As can be seen from Fig. 5.8, both BER curves do not decrease significantly when $N_t > 4000$. It can be concluded that the value of E_b/N_0 does not affect the selection of interleaver size and the optimum selection of interleaver size under different E_b/N_0 are similar.

Figure 5.9: BER performance provided by the proposed iterative receiver over a flat fading channel characterized by $f_d T = 0.001$

5.5.3 Performance of the Proposed Iterative Receiver

Figs. 5.9 and 5.10 show the BER performance provided by the proposed SISO demodulator with different numbers of iterations over flat fading channels with $f_d T = 0.001$ and $f_d T = 0.01$, respectively. The performance with known channel conditions is also included in these figures for comparison. The notation ‘*Iterations*’ refers to the number of iterations. The frame length is 32 symbols containing one pilot symbol for initialization. The AR model order is one and the observation interval is 2. Several observations can be inferred from the figures. First of all, the largest performance gap in both figures occurs between the 0^{th} iteration and the 1^{st} iteration. Secondly, performance can be improved through iterations. However, the performance improvement after the 5^{th} iteration is marginal. For this reason, performance curves beyond the 5^{th} iteration are not shown. Finally, the performance improvement via iterations is more significant when E_b/N_0 is

Figure 5.10: BER performance provided by the proposed iterative receiver over a flat fading channel characterized by $f_d T = 0.01$

high. When E_b/N_0 is low, the information fed back as a priori knowledge to the SISO demodulator is less reliable and hence does not improve the performance much.

Fig. 5.11 shows the MSE of channel estimates with different number of iterations. $f_d T = 0.001$ and 0.01 are considered. The settings of this figure are the same as those of Fig. 5.9 and 5.10. In the proposed SISO demodulator, the detected data are assumed to be correct in channel tracking. As shown in Fig. 5.9 and 5.10, through iterations, the accuracy of data detection can be improved and this will further refine the accuracy of the channel estimates. As expected, the MSE of channel estimates reduces through iterations. It is interesting to note that the BER performance and the MSE of channel estimates are consistent with each other. Figs. 5.9 and 5.10 also show that, when $E_b/N_0 \leq 4$ dB, the BER curves do not change as the number of iterations increases. This also happens in Fig. 5.11. Furthermore, the accuracy of channel estimation is inversely proportional to the channel fading rate $f_d T$.

Figure 5.11: MSE of channel estimates versus E_b/N_0 for a different number of iterations with $f_d T = 0.001$ and $f_d T = 0.01$

5.5.4 Performance Comparison

As mentioned before, the PSP based SISO-FO algorithm performs better than SISO-FB algorithm [2]. So we only compare the proposed demodulator with PSP based SISO-FO and SEP based SISO algorithms. As can be seen from Fig. 5.12, the proposed SISO demodulator provides a 0.8 dB gain over the PSP based SISO algorithm and 1.5 dB gain over SEP based SISO algorithm at $BER = 10^{-3}$. Similar with the hard output demodulator proposed in Chapter 4, the computational complexity of the proposed SISO demodulator slightly increases to $O(L_o p M^L)$ while the complexity of PSP-SISO and SEP-SISO is $O(p M^L)$.

Figure 5.12: Performance comparison among the proposed SISO demodulator, the PSP based A-SISO-FO in [1] and the SEP based A-SISO in [2]

5.6 Summary

In this chapter the hard output demodulator proposed in Chapter 4 had been extended to a novel SISO demodulator for SCCPM signals. The proposed demodulator mainly consists of two parts: a truncated BCJR algorithm and a KF based channel estimator. These two parts exchange and update information in every symbol interval. Due to its abilities of incorporating a priori symbol probabilities and outputting soft decisions, the proposed SISO demodulator is well suited for an iterative receiver. The convergence behavior and the effects of the interleaver size had been analyzed. BER comparisons with existing algorithms had been presented to evidence the efficacy of the proposed algorithm.

Chapter 6

Joint Data Detection and Channel Estimation for Orthogonal Space-Time Block Coded CPM

In Chapter 5, we have investigated the data detection and channel estimation for SCCPM signals. It has been shown that, if an iterative receiver is used, the proposed scheme can achieve satisfactory performance even at a low value of E_b/N_0 . However, the complexity of decoding convolutional codes (CCs) is relatively high. Therefore, it is important to find an encoding scheme which improves the reliability of data transmission while having a simple decoder. OSTBCs [52], which exploit the diversity gain provided by multiple transmit/receive antennas, satisfy this requirement. Both OSTBCs and CCs rely on increasing the redundancy of transmit sequences. However, OSTBCs do not provide coding gain as CCs but only provide diversity gain. Relying on the orthogonality of transmit signals through different antennas and multiple time slots, decoding OSTBCs is much simpler than decoding convolutional codes. In this chapter, we concentrate on the problem of joint data detection and channel estimation for orthogonal space-time block coded CPM signals over quasi-static flat fading channels. The proposed framework consists of two parts: a novel block construction using tail sequences for ensuring phase continuity at the transmitter and a new technique for joint data detection and channel estimation at the receiver. Due to the

requirement of phase continuity and the associated inherent memory of CPM, the combination of OSTBC with CPM is not as straightforward as with linear modulation schemes. First, to ensure phase continuity, a tail sequence is inserted at the end of each block so that the end phase of every block satisfies certain constraints. Then by assuming that channel is quasi-static, the EM algorithm is applied for channel estimation for the orthogonal space-time block coded CPM signals and the resulting channel information is used for evaluating the APP for transmitted CPM signals in the data detection part. These two steps run iteratively. Initial channel estimates are extracted from a small number of pilots for preventing channel divergence. Simulation results show that the proposed method can preserve the bandwidth efficiency of CPM signals and that the proposed iterative receiver will significantly outperform its non-iterative counterpart. Note that a quasi-static assumption is necessary for OSTBC decoding. This assumption represents an essential difference between the method discussed in this chapter and those illustrated in Chapters 4 and 5.

6.1 Introduction

Mitigating fading effects is one of the most challenging work in wireless communications. Space-time coding can exploit the capacity gains by exploiting the fact that signals from different antennas are unlikely to experience deep fading simultaneously. In the last few years some works have been done to extend space-time coding originally developed for linear modulation schemes to CPM. Design rules for space-time trellis coded CPM were first proposed in [56]. After that, improved works on space-time trellis coded CPM have been developed in [57, 58], etc. Due to the inherent memory in CPM signals and the memory between antennas introduced by STTCs, the decoding complexity of the resulting space-time coded CPM could be high. For simplicity, we consider orthogonal space-time block coded CPM in this chapter. It has been pointed out in [56] that OSTBCs cannot be gener-

alized to CPM signal easily as both orthogonality and phase continuity should be achieved simultaneously.

In this chapter, an orthogonal space-time block coded CPM transmitted over an unknown time-varying block fading channel is proposed by modifying Alamouti's scheme. We consider two main objectives in orthogonal space-time block coded CPM system design: the bandwidth efficiency at the transmitter and the accuracy of data detection at the receiver.

To achieve the first objective, in [60] waveform modifications have been made in every symbol period to make the CPM waveforms transmitted over different antennas satisfy certain constraints at neighboring symbol intervals. This is to ensure the phase continuity and orthogonality. However, due to the symbol-by-symbol processing and the inherent memory of CPM, the design of orthogonal schemes is quite complicated especially when partial response CPM is adopted. In [61] a simple receiver based on the Laurent's decomposition of orthogonal space-time block coded CPM is derived and a linear minimum mean square error (MMSE) filter is used to cancel out the interference among antennas. However, this solution is only applicable to binary CPM with modulation index $h = 0.5$. A burst-based orthogonal space-time block coding scheme has been proposed in [62]. A guard interval is inserted between consecutive blocks to minimize the impact of the transition from one block to the next one. This method is simple and straightforward but some bandwidth efficiency is lost because the phase continuity of CPM is not guaranteed during the transition between blocks. In [63] redundant symbols are inserted to ensure the phase continuity for orthogonal space-time block coded CPM signals transmitted over frequency selective fading channels.

The decoding of the above orthogonal space-time block coded CPM schemes assumes the availability of accurate channel information at the receiver. However, this assumption is not realistic for a practical wireless communication system and inaccurate channel information may cause large errors in data detection. Therefore, to achieve the second objective, a

solution to the joint optimization problem of channel estimation and data detection is needed. Usually a direct optimization will suffer from high computational burden. A widely adopted suboptimal solution is to divide the problem into a set of optimization tasks, one for each unknown parameter. The soft information from each part is exchanged in an iterative manner and, if a proper initial value is chosen, a near optimal result may be obtained after several iterations. This method is referred to as iterative processing or turbo processing. The EM algorithm is a general method for iterative processing and has been applied to a large number of communication problems. In [64, 65] an EM-based receiver was proposed for OSTBC-OFDM systems. The shortcoming of this approach is the necessity of channel statistics and the extra computational load. For a single antenna channel, an EM-based channel estimation for CPM signals has been proposed in [66]. In this chapter, this approach is extended to the detection of orthogonal space-time block coded CPM. To the best of author's knowledge, this is the first time that the problem of joint data detection and channel estimation was investigated for orthogonal space-time block coded CPM systems.

In the following, a framework to achieve bandwidth efficiency and accurate data detection for orthogonal space-time block coded CPM systems simultaneously is proposed. The proposed framework primarily contains two features to achieve the above mentioned objectives. First of all, at the transmitter side, a novel block construction using a tail sequence is proposed to ensure that no bandwidth efficiency is lost for orthogonal space-time block coded CPM. To ensure phase continuity, a tail sequence at the end of every block is used to force the phase return to a desired state. Compared with [60], where the evaluation of tail sequences for each antenna is independent and separated, in the proposed method tail sequences for two antennas within a single block are the same; this makes the evaluation of the tail sequence is necessary for one antenna only. In particular, the proposed method can be applied to any CPM format. Secondly, at the receiver side, a joint iterative data detection and channel estimation scheme is proposed for orthogonal space-time block coded CPM

over unknown block fading channels. In doing so, we first derive a ML channel estimate via the EM algorithm in which the state transition probabilities from the previous iteration are used in the E step as the a priori information. It is shown that because of the assumption that the channel remains constant in one frame and has no memory (flat fading), the complexity of the resulting channel updating is proportional to the frame length. The refined channel estimates are fed to the BCJR algorithm [7] which evaluates state transition probabilities. Unlike usual iterative algorithms, the soft information provided here is the state transition probability (instead of the symbol probability). The E and M steps are iterated until satisfactory performance is achieved.

6.2 Preliminary

In this section, we briefly introduce the fundamental concepts of Alamouti code [52] and EM algorithm which will be used in the subsequent sections.

6.2.1 Orthogonal Space-Time Block Coding

Alamouti discovered a simple scheme for which ML detection involves linear processing at the receiver [52]. This scheme is very attractive and is a part of both the W-CDMA and CDMA-2000 standards. Tarokh extended the case of Alamouti's two transmit antennas to an arbitrary number of transmit antennas [54]. Let h_1 and h_2 denote the channel gains from transmit antennas 1 and 2 to the receive antenna, respectively. The gains h_1 and h_2 are assumed to be constant over two consecutive symbol periods [52]. The input symbols to the OSTBC encoder are split into two-symbol groups, i.e., $\{i_1, i_2\}$. During the first time slot, i_1 and i_2 are transmitted simultaneously from antenna 1 and antenna 2, respectively. In the next symbol period, $-i_2^*$ is transmitted from antenna 1 and i_1^* is transmitted from antenna 2 [52]. The received signals over two consecutive symbol periods are denoted r_1 and r_2 , respectively. By computing the conjugate of r_2 and defining the received signal

vector $\mathbf{r} \triangleq [r_1 \ r_2^*]^T$, the code symbol vector $\mathbf{i} \triangleq [i_1 \ i_2]^T$ and the noise vector $\mathbf{n} \triangleq [n_1 \ n_2^*]^T$, we obtain

$$\mathbf{r} = \mathbf{H}\mathbf{i} + \mathbf{n}. \quad (6.1)$$

The vector $\mathbf{n}$ is a complex Gaussian random vector with zero mean and covariance matrix $N_0\mathbf{I}_2$ ($\mathbf{I}_2$ is the 2×2 identity matrix) and the channel matrix $\mathbf{H}$ is defined as [52]

$$\mathbf{H} \triangleq \begin{bmatrix} h_1 & h_2 \\ h_2^* & -h_1^* \end{bmatrix}. \quad (6.2)$$

The most significant advantage of OSTBC over STTC is that by using the orthogonality of OSTBC, ML decoding can be further simplified. We have that

$$\mathbf{H}^*\mathbf{H} = (|h_1|^2 + |h_2|^2)\mathbf{I}_2. \quad (6.3)$$

By multiplying $\mathbf{H}^*$ on both sides of Eq. (6.1), the modified received signal is given by

$$\tilde{\mathbf{r}} = \mathbf{H}^*\mathbf{r} = (|h_1|^2 + |h_2|^2)\mathbf{i} + \tilde{\mathbf{n}}, \quad (6.4)$$

where $\tilde{\mathbf{n}} = \mathbf{H}^*\mathbf{n}$. Then the decoding rule can be reduced to two separate, linear equations, one for each symbol. If the constellation has 2^b points, the decoding complexity of ML can be reduced from 2^{2b} to 2^{b+1} .

6.2.2 EM Algorithm

The ML estimation of φ based on an observed sequence $\mathbf{y}$ is given by

$$\hat{\varphi}_{ML} = \arg \max_{\varphi} f(\mathbf{y} | \varphi). \quad (6.5)$$

If the function $f(\mathbf{y} | \varphi)$ depends also on the unobserved variables, a direct evaluation of $\hat{\varphi}_{ML}$ is impossible. If we consider another unobserved variable $\mathbf{x}$ which also depends on $\mathbf{y}$, we have

$$f(\mathbf{y} | \varphi) = \int f(\mathbf{y}, \mathbf{x} | \varphi) d\mathbf{x}. \quad (6.6)$$

The choice of $\mathbf{x}$ should make the derivation of $f(\mathbf{y}, \mathbf{x} | \varphi)$ simpler. After evaluating the likelihood function $\int f(\mathbf{y}, \mathbf{x} | \varphi) d\mathbf{x}$, the derivatives of the likelihood function with respect to φ and $\mathbf{x}$ are set to 0. These equations need to be solved simultaneously to obtain φ . However, these equations are usually interlocked and difficult to solve.

The EM algorithm is an iterative method to solve the above described problem. It usually consists of two steps. The first step is the expectation step which computes the auxiliary function on the basis of the previous estimation. The second one is a maximization step. These steps are iterated until a satisfactory φ is found. Note that EM algorithm can only find a local maximum of $f(\mathbf{y} | \varphi)$. To guarantee that it finds the global maximum, the initial φ should be selected to be close to the global maximum if $f(\mathbf{y} | \varphi)$ has multiple local maxima.

A detailed derivation of the EM algorithm can be found in [72]. It consists of the following steps:

1. initialization of φ ;
2. set $q = 0$ where q is the number of iteration;
3. evaluate the auxiliary function

$$Q(\varphi | \varphi^{(q)}) = \int \log f(\mathbf{y}, \mathbf{x} | \varphi) f(\mathbf{x} | \mathbf{y}, \varphi) d\mathbf{x}; \quad (6.7)$$

4. find $\varphi^{(q+1)}$ which maximizes $Q(\varphi | \varphi^{(q)})$ and increase q by one;
5. step 3 and 4 are iterated until $|\varphi^{(q)} - \varphi^{(q-1)}| < \varepsilon$ where ε is a very small positive value.

6.3 System Model

The block diagram of the transmitter and the receiver of an orthogonal space-time block coded CPM system is depicted in Fig. 6.1. To make the phase of the orthogonal space-time block coded CPM signals continuous between consecutive blocks, tail sequences at the end

Figure 6.1: Block diagram of transmitter and receiver for orthogonal space-time block coded CPM systems.

of each block will be inserted. The output of the block construction is sent to a continuous phase modulator. The space-time block encoder takes the CPM signals as its input and outputs the orthogonal space-time block coded CPM signals. The transmitted signal is then passed through a quasi-static flat fading channel which changes from block to block but remains constant within a block. The proposed receiver consists of three modules: an OS-TBC decoder, a MAP demodulator based on the BCJR algorithm and a channel estimator based on the EM algorithm. Through iterations, the information exchanged between the MAP demodulator and the channel estimator can be made more reliable to improve system performance.

6.4 A Novel Block Construction based on Tail Sequences for Orthogonal Space-Time Block Coded CPM

In this section a block construction method is proposed, which makes the use of orthogonal space-time block coding for CPM possible without a loss of bandwidth efficiency. The proposed approach is an extension of the approach in [63, 99] which uses redundant symbols to keep phase continuity for CPM in frequency domain equalization .

Figure 6.2: The proposed block construction structure.

Figure 6.3: Phase rotation at antenna 1 for 4 consecutive blocks.

Figure 6.4: Phase rotation at antenna 2 for 4 consecutive blocks.

For simplicity, only Alamouti code is considered in this chapter. Alamouti code is a typical OSTBC which achieves full diversity and has a simple decoding algorithm. We use a subscript k to denote the parameters referring to the k th frame; each frame is composed of two consecutive blocks given as $\mathbf{X}_k = \{\mathbf{x}_{2k}, \mathbf{x}_{2k+1}\}$. Each block has a length equal to N_d ; the k th block is $\mathbf{x}_k = \{x_k(1), x_k(2), \dots, x_k(N_d)\}$. Note that each entry of the Alamouti encoding matrix here is not a single symbol, but the modulated CPM signals referring to a block. Thus, the corresponding encoding matrix is

$$\begin{bmatrix} \mathbf{x}_{2k} & \mathbf{x}_{2k+1} \\ -\mathbf{x}_{2k+1}^* & \mathbf{x}_{2k}^* \end{bmatrix}, \quad (6.8)$$

where each column represents the transmissions from two antennas during a given time slot while each of the two rows represents two consecutive transmitted CPM blocks on a given antenna. Notation $(.)^*$ denotes the complex conjugation. We assume that the channel is quasi-static, i.e., it changes from frame to frame, but remains constant within each frame. Due to this assumption, the orthogonality of the above encoding matrix is maintained. In Eq. (6.8), the conjugate operation on the transmitted CPM signal results in a change of the sign of its imaginary part while the negative sign produces a 180° phase shift. Therefore, when Alamouti encoding rule is applied directly to CPM, the phase functions associated with antenna 2 can be related with those of antenna 1 as

$$\begin{aligned} \phi_2(t) &= -\phi_1(t + N_d T, \mathbf{a}_{2k+1}) + \pi \\ \phi_2(t + N_d T) &= -\phi_1(t, \mathbf{a}_{2k}) \end{aligned}, \quad (6.9)$$

where $\mathbf{a}_l = \{a_1^l, a_2^l, \dots, a_{N_d}^l\}$ represents the sequence of transmitted symbol in the l th block. As shown in Eq. (6.9), the phase of antenna 2 signals is the opposite to the phase of antenna 1 signals. Moreover, the phase for the $(2k)$ th block of antenna 2 signals is reversed in time with respect to the phase of the $(2k + 1)$ th block of antenna 1 signals. Therefore, phase continuity cannot be guaranteed for antenna 2 signals. To overcome this problem and

deploy the CPM scheme in an orthogonal space-time block coded system, the proposed method ensures phase continuity for the signals of both antennas at interblock transitions.

The proposed method for novel block construction is shown in Figure 6.2. We use a finite length tail sequence to shift phase from any phase state to the zero phase state which is represented by [63]

$$\{\theta_n = 0, a_{n-L+1} = 0, a_{n-L+2} = 0, \dots, a_{n-1} = 0\} \quad (6.10)$$

or to the π phase state which is represented by

$$\{\theta_n = \pi, a_{n-L+1} = 0, a_{n-L+2} = 0, \dots, a_{n-1} = 0\}, \quad (6.11)$$

where L is the CPM correlation length. The constructed tail sequence consists of two parts. The first part is used to shift the cumulative phase state to the desired phase 0 or π ; whereas the second part which contains $L - 1$ zero symbols is used to cancel out the effects of the previous block on the current block and to ensure that the phase at the end of each block is equal to the cumulative phase θ_n .

The desired phase rotation for signals transmitted by antenna 1 is shown in Figure 6.3. Note that four consecutive blocks (that is two consecutive frames) are processed as a group, denoted as $\{\mathbf{x}_{2k}, \mathbf{x}_{2k+1}, \mathbf{x}_{2k+2}, \mathbf{x}_{2k+3}\}$. The tail sequence at the end of block $2k$ has to shift the phase to π while the initial state of block $2k$ is 0. After the first block, the subsequent block starts at state π and ends at π ; this is achieved by inserting the tail sequence $2k + 1$. During block $2k + 2$, the state transition starts at π and is followed by the tail sequence $2k + 2$ to let the state go to and stay at 0. Finally, the initial state of block $2k + 3$ is 0 and the tail sequence $2k + 3$ is used to force the state back to 0. When the signal on antenna 1 undergoes the above phase transition, the signal phase of antenna 2 can be guaranteed to be continuous between adjacent blocks. The phase transition of the signal transmitted

by antenna 2 is shown in Figure 6.4. Therefore, no additional computation is needed for antenna 2 and this reduces the transmitter complexity.

Note that the length of transmitted data for every block is N_d . The subsequent $N_p - N_d$ elements constitute of the first part of tail sequence which is used to shift the cumulative phase to the desired one. After inserting the tail sequence, we denote the length of the expanded block as N_T . Thus N_d and $N_T - N_d$ represent the length of the information sequence and that of the tail sequence within a block, respectively. The phase at the end of the N_p th interval is

$$\phi_{N_T}^k \triangleq \phi^k(N_T T, \mathbf{a}) = \phi_{N_T}^{k-1} + \pi h \sum_{i=0}^{N_T-L} a_i^k + 2\pi h \sum_{m=0}^{L-1} a_{N_T-m}^k q(mT). \quad (6.12)$$

According to the proposed block construction,

$$\left\{ a_{N_p}^k = 0, a_{N_p+1}^k = 0, \dots, a_{N_T-1}^k = 0 \right\}. \quad (6.13)$$

where the superscript k denotes the block index. Then, substituting Eq. (6.13) into Eq. (6.12) produces

$$\phi_{N_T}^k = \phi_{N_T}^{k-1} + \pi h \sum_{i=0}^{N_T-L} a_i^k = \pi h \sum_{l=0}^{k-1} \sum_{n=0}^{N_T-1} a_n^l + \pi h \sum_{i=0}^{N_T-L} a_i^k. \quad (6.14)$$

The phase evaluated above includes all the symbols up to the interval N_p in block k . For each block we assume that the modulator remembers the state after the $(k-1)$ th block and starts to modulate the k th block from that state; this means that $\phi_0^{k+1} = \phi_{N_T}^k$. The proposed method has a fixed initial cumulative phase which is equal to the initial instantaneous phase of each block. The initial instantaneous phase values are given by

$$\{ \phi_0^{2k} = 0, \phi_0^{2k+1} = \pi, \phi_0^{2k+2} = \pi, \phi_0^{2k+3} = 0 \}. \quad (6.15)$$

The reason for this fixed initial phase arrangement is that, after orthogonal space-time block coding, on the basis of Eq. (6.9), the initial phase of antenna 2 will have the corresponding values

$$\{ \phi_0^{2k} = 0, \phi_0^{2k+1} = 0, \phi_0^{2k+2} = \pi, \phi_0^{2k+3} = \pi \}. \quad (6.16)$$

As indicated by the above two equations, the phase of antenna 2 will be guaranteed to be continuous without requiring any additional evaluation of its tail sequences. This is simpler than [63], where phase continuity is maintained by two different tail sequences for each antenna. The detailed method for evaluation of the tail symbols is similar to the one in [99] where a block is inserted for enabling frequency domain equalization (FDE) with CPM. When the final phase is 0 and π , we have that

$$(\phi_0^k + \pi h (\sum_{i=0}^{N_d-1} a_i^k + \sum_{i=N_d}^{N_p-1} a_i^k)) \mod 2\pi = 0 \quad (6.17)$$

and

$$(\phi_0^k + \pi h (\sum_{i=0}^{N_d-1} a_i^k + \sum_{i=N_d}^{N_p-1} a_i^k)) \mod 2\pi = \pi, \quad (6.18)$$

where $\mod x$ is the modulo x operator. These two equations provide a method for calculating the tail symbols under different start and end phase requirements. The symbols in tail sequence are used to make the end phase of each block satisfy the constraints (6.15) and (6.16). For partial response CPM, additional $L - 1$ zero symbols should be inserted to remove the effect of the previous block propagating into the current block.

When transmitting N_d useful data, a tail sequence with length $\bar{N}$ is required for phase continuity. Therefore, the throughput loss can be represented by $R_L = \frac{\bar{N}}{N_d + \bar{N}}$. $\bar{N} = p + L - 1$ is sufficient to shift the phase state from any phase state to the wanted 0 state or π state, thereby ensuring the phase continuity between blocks. For the widely used CPM formats, $\bar{N}$ is typically very small, e.g., $\bar{N}$ equals to 1 for MSK signal which has $h = 1/2$,

$L = 1$ and rectangular frequency pulse. Therefore, when $N_d \gg \bar{N}$, the throughput loss could be negligible.

It is important to emphasize the difference between the proposed method with the one in [63] which also addresses the same problem under a frequency selective channel between transmit antenna and the receive antenna. The authors in [63] propose a block construction preserving phase continuity between antennas and successive blocks. However, the evaluation of tail sequences for each antenna is independent. In the proposed method, the tail sequences for the two antennas within one block are the same; this reduces the computational complexity at the transmitter especially when the block length is large. Note that phase continuity between blocks is important for channel tracking in time-varying channels as discussed in [100]. Moreover, in [63] the channel is assumed to be known while in this work the channel is unknown and quasi-static. The proposed channel estimation method is discussed in the following section.

6.5 Receiver Structure

6.5.1 Decoding of OSTBC

We assume that all the channels are frequency-flat and quasi-static. When the Alamouti STBC is applied, two consecutive $((2k)\text{th}$ and $(2k+1)\text{th}$) blocks as in Eq.(6.9), are defined for every $k\text{th}$ frame. Let $y_k(n)$ denote the received signal for the $k\text{th}$ block in the $(N_d \times k + n)\text{th}$ symbol interval where $n = 1, 2, \dots, N_d$ and N_d is the block length. The received signal for the $k\text{th}$ frame $\mathbf{Y}_k$ can be expressed as

$$\mathbf{Y}_k = \mathbf{X}_k \mathbf{H}_k + \mathbf{N}_k \quad (6.19)$$

with

$$\begin{aligned}
 \mathbf{Y}_k &\triangleq [y_{2k}(1), y_{2k+1}(1), \dots, y_{2k}(N_d), y_{2k+1}(N_d)]_{2N_d \times 1}^T, \\
 \mathbf{X}_k &\triangleq [X_k(1), X_k(2), \dots, X_k(N_d)]_{2N_d \times 2}^T, \\
 X_k(i) &\triangleq \begin{bmatrix} x_{2k}(i) & x_{2k+1}(i) \\ -(x_{2k+1}(i))^* & (x_{2k}(i))^* \end{bmatrix}, \\
 \mathbf{H}_k &\triangleq [h_{1k} \ h_{2k}]^T.
 \end{aligned} \tag{6.20}$$

Here $\mathbf{X}_k$ is the $2N_d \times 2$ orthogonal space-time block coded CPM associated with the k th frame, $x_m(i)$ is the CPM signal transmitted for the m th block in the $(m \times N_d + i)$ th symbol interval, h_{ik} is the complex channel gain for the i th antenna over the k th frame, $\mathbf{N}_k$ is a $N_d \times 2$ noise vector whose entries are independent Gaussian random variables.

We have shown the representation of the received signals for the k th frame. If N consecutive frames are considered, the overall received signal is given by

$$\mathbf{Y} = \mathbf{X}\mathbf{H} + \mathbf{N} \tag{6.21}$$

with

$$\begin{aligned}
 \mathbf{Y} &\triangleq [\mathbf{Y}_1^T, \mathbf{Y}_2^T, \dots, \mathbf{Y}_N^T]_{2NN_d \times 1}^T, \\
 \mathbf{X} &\triangleq \text{diag}\{\mathbf{X}_1, \mathbf{X}_2, \dots, \mathbf{X}_N\}_{2NN_d \times 2N}, \\
 \mathbf{H} &\triangleq [\mathbf{H}_1^T, \mathbf{H}_2^T, \dots, \mathbf{H}_N^T]_{2N \times 1}^T.
 \end{aligned} \tag{6.22}$$

Note that $\mathbf{X}$ is an orthogonal matrix, since $\mathbf{X}\mathbf{X}^H = 2\mathbf{I}_{2NN_d \times 2NN_d}$. When the channel matrix $\mathbf{H}$ is known, the decoding of OSTBC can be accomplished as illustrated in [52]. In the following we show how joint data detection and channel estimation can be achieved.

6.5.1.1 Initialization of the EM Algorithm

The EM algorithm is sensitive to the accuracy of the initial value. Hence, we use pilot symbols to guarantee that the initial value is close to the global maximum. We define a pilot block which has a similar structure as shown in Figure 6.4 and define the corresponding received signals, input signals and the estimated initial channel coefficients as $\mathbf{Y}_{pilot}$, $\mathbf{X}_{pilot}$ and $\mathbf{H}_0$, respectively. A least square estimator provides the initial value

$$\mathbf{H}^{(0)} = (\mathbf{X}_{pilot}^H \mathbf{X}_{pilot})^{-1} \mathbf{X}_{pilot}^H \mathbf{Y}_{pilot}, \tag{6.23}$$

where $\mathbf{X}_{pilot}$ is a $L_p \times 2$ matrix and L_p is the pilot length smaller than N_b . The orthogonality of the matrix $\mathbf{X}_{pilot}$ and the unit amplitude of CPM signals lead to $(\mathbf{X}_{pilot}^H \mathbf{X}_{pilot})^{-1} = \mathbf{I}/2$ where $\mathbf{I}$ is 2×2 identity matrix. Since no matrix inversion is involved here, the complexity of the initialization is low. The frequency of pilot insertion usually represents a tradeoff between system performance and the throughput.

6.5.1.2 The EM Step

We consider orthogonal space-time block coded CPM signals of the k th frame as the hidden variables for which statistical information can be attained from the previous MAP demodulation procedure. Following [65], the auxiliary function Q is

$$\begin{aligned} Q(\mathbf{H}_k | \mathbf{H}_k^q) &= \sum_{\bar{\mathbf{X}}_k} \log \Pr(\mathbf{Y}_k, \mathbf{X}_k | \mathbf{H}_k) \Pr(\mathbf{X}_k | \mathbf{Y}_k, \mathbf{H}_k^q) \\ &= \sum_{\bar{\mathbf{X}}_k} (\log \Pr(\mathbf{Y}_k | \mathbf{X}_k, \mathbf{H}_k) + \log \Pr(\mathbf{X}_k | \mathbf{H}_k)) \Pr(\mathbf{X}_k | \mathbf{Y}_k, \mathbf{H}_k^q) \quad . \end{aligned} \quad (6.24)$$

Since $\mathbf{X}_k$ is independent of $\mathbf{H}_k$, the term of $\sum_{\bar{\mathbf{X}}_k} \log \Pr(\mathbf{X}_k | \mathbf{H}_k) \Pr(\mathbf{X}_k | \mathbf{Y}_k, \mathbf{H}_k^q)$ does not involve $\mathbf{H}_k$ and hence can be ignored in Eq. (6.24). Moreover, since $E(\mathbf{N}_k \mathbf{N}_k^H) = \sigma_n^2 \mathbf{I}$, when $\mathbf{X}_k$ and $\mathbf{H}_k$ are conditionally known, $\Pr(\mathbf{Y}_k | \mathbf{H}_k, \mathbf{X}_k)$ in Eq. (6.24) is given by

$$\begin{aligned} &\Pr(\mathbf{Y}_k | \mathbf{H}_k, \mathbf{X}_k) \\ &= \frac{1}{\det(2\pi\sigma_n^2 \mathbf{I})} \exp \left[-\frac{(\mathbf{Y}_k - \mathbf{X}_k \mathbf{H}_k)^H (\mathbf{Y}_k - \mathbf{X}_k \mathbf{H}_k)}{2\sigma_n^2} \right] \\ &= \prod_{n=1}^{N_d} \frac{1}{2\pi\sigma_n^2} \exp \left[-\frac{1}{2\sigma_n^2} (d_{2k}(n) + d_{2k+1}(n)) \right], \end{aligned} \quad (6.25)$$

where

$$\begin{aligned} d_{2k}(n) &= |y_{2k}(n) - h_{1,k}x_{2k}(n) - h_{2,k}x_{2k+1}(n)|^2, \\ d_{2k+1}(n) &= |y_{2k+1}(n) + h_{1,k}(x_{2k+1}(n))^* - h_{2,k}(x_{2k}(n))^*|^2. \end{aligned} \quad (6.26)$$

In the following the quantity $\Pr(\mathbf{X}_k | \mathbf{Y}_k, \mathbf{H}_k^q)$ denotes the APP of interest. Usually in the modulation schemes without memory, such as BPSK and QAM, the APP admits the simple expansion $\Pr(\mathbf{X}_k | \mathbf{Y}_k, \mathbf{H}_k^q) = \prod_{n=1}^{N_d} \Pr(x_k(n) | y_k(n), \mathbf{H}_k^q)$ because of the independence among transmitted signals. However, this is not the case in CPM signals in which

signals over different symbol intervals are correlated. To proceed, by using the definition of conditional probability density function, a recursive equation can be derived as

$$\Pr(\mathbf{X}_k | \mathbf{Y}_k, \mathbf{H}_k^q) = \prod_{n=1}^{N_d} \Pr(x_k(n) | x_k(n-1), \dots, x_k(1), \mathbf{Y}_k, \mathbf{H}_k^q). \quad (6.27)$$

Unlike the APP in OFDM [64, 65], the one in Eq. (6.27) is not the APP of the transmitted symbols but is that of the modulated signals. Moreover, $\Pr(x_k(n) | x_k(n-1), \dots, x_k(1), \mathbf{Y}_k, \mathbf{H}_k^q)$ is related to the whole CPM signals before the n th time. Fortunately, this quantity can be provided by the previous data detection part using BCJR algorithm for every n th symbol in the k th block. Detailed evaluation of this APP will be described later. To simplify the notation, let $\Pr(x_k(n) | x_k(n-1), \dots, x_k(1), \mathbf{Y}_k, \mathbf{H}_k^q) = \Pr(x_k(n))$. Then, since the signals transmitted in the two packets of the same block are independent, the posteriori probability can be expressed as

$$\Pr(\mathbf{X}_k | \mathbf{Y}_k, \mathbf{H}_k^q) = \prod_{n=1}^{N_d} \Pr(x_{2k}(n)) \prod_{n=1}^{N_d} \Pr(x_{2k+1}(n)). \quad (6.28)$$

$$\begin{aligned} Q(\mathbf{H}_k | \mathbf{H}_k^q) &= \sum_{\bar{\mathbf{x}}_{2k}, \bar{\mathbf{x}}_{2k+1}} \left\{ \left(- \sum_{n=1}^{N_d} \left[\frac{1}{2\sigma^2} (d_{2k}(n) + d_{2k+1}(n)) - \frac{1}{2} \log 2\pi\sigma^2 \right] \right) \right. \\ &\quad \times \left. \prod_{n=1}^{N_d} \Pr(x_{2k}(n)) \prod_{n=1}^{N_d} \Pr(x_{2k+1}(n)) \right\} \\ &= -\frac{1}{2\sigma^2} \sum_{n=1}^{N_d} \sum_{\bar{\mathbf{x}}_{2k}, \bar{\mathbf{x}}_{2k+1}} [(d_{2k}(n) + d_{2k+1}(n)) \Pr(x_{2k}(n)) \Pr(x_{2k+1}(n))] - \frac{N_d}{2} \log 2\pi\sigma^2 \end{aligned} \quad (6.29)$$

Substituting Eq. (6.28) and Eq. (6.25) into Eq. (6.24), produces two auxiliary functions shown in Eq. (6.29). The exchange of the two summations in the second step of Eq. (6.29) will significantly reduce the computational complexity. The summation is carried out over all the possible CPM sequences lasting N_d symbol intervals, and there are pM^L possible CPM signals per symbol interval. Thus the number of possible CPM sequences

over N_d symbol intervals is $(pM^L)^{N_d}$. However, after exchanging the positions of the two summations, the total number of the overall possible sequences is $N_d(pM^L)^2$.

Eq. (6.29) can be further simplified by separating $\sum_{\bar{\mathbf{x}}_{2k}, \bar{\mathbf{x}}_{2k+1}} ()$ into $\sum_{\bar{\mathbf{x}}_{2k}} ()$ and $\sum_{\bar{\mathbf{x}}_{2k+1}} ()$. After this separation, the cross term $\sum_{\bar{\mathbf{x}}_{2k}, \bar{\mathbf{x}}_{2k+1}} (d_{2k} + d_{2k+1})$ is canceled out and two separate parts are found. The first part is related to $\bar{\mathbf{x}}_{2k}$ only and is

$$\sum_{\bar{\mathbf{x}}_{2k}} (|y_{2k}|^2 - h_{1k}^* x_{2k}^* y_{2k} - h_{1k} x_{2k} y_{2k}^* + |h_{1k}|^2 |x_{2k}|^2 - h_{2k}^* x_{2k} y_{2k+1} - h_{2k} x_{2k}^* y_{2k+1}^* + |h_{2k}|^2 |x_{2k}|^2), \quad (6.30)$$

whereas the second part is

$$\sum_{\bar{\mathbf{x}}_{2k+1}} (|y_{2k+1}|^2 - h_{2k}^* x_{2k+1}^* y_{2k} - h_{2k} x_{2k+1} y_{2k}^* + |h_{2k}|^2 |x_{2k+1}|^2 + h_{1k}^* x_{2k+1} y_{2k+1} + h_{1k} x_{2k+1}^* y_{2k+1}^* + |h_{1k}|^2 |x_{2k+1}|^2), \quad (6.31)$$

which is a function of $\bar{\mathbf{x}}_{2k+1}$ only. This separation results from the orthogonality of Alamouti code. According to the law of total probability, we have

$$\sum_{\bar{\mathbf{x}}_{2k}, \bar{\mathbf{x}}_{2k+1}} (d_{x_{2k}} + d_{x_{2k+1}}) \Pr(x_{2k}) \Pr(x_{2k+1}) = \sum_{\bar{\mathbf{x}}_{2k}} d_{x_{2k}} \Pr(x_{2k}) + \sum_{\bar{\mathbf{x}}_{2k+1}} d_{x_{2k+1}} \Pr(x_{2k+1}). \quad (6.32)$$

This step further reduces the computational complexity from $N_d(pM^L)^2$ per block to $N_d pM^L$ for the evaluation of $\mathbf{H}_k$ in every block. Based on the derivation above, the auxiliary function takes the form

$$Q(H_k | H_k^q) = -\frac{1}{2\sigma^2} \sum_{n=1}^{N_d} \left(\sum_{\bar{\mathbf{x}}_{2k}} d_{x_{2k}}(n) \Pr(x_{2k}(n)) + \sum_{\bar{\mathbf{x}}_{2k+1}} d_{x_{2k+1}}(n) \Pr(x_{2k+1}(n)) \right). \quad (6.33)$$

In the M step, the estimate of $\mathbf{H}_k^{q+1}$ which maximizes $Q(\mathbf{H}_k | \mathbf{H}_k^q)$ needs to be evaluated. To do this, the derivative of $Q(\cdot)$ is set to 0. After solving equation $\frac{dQ(\mathbf{H}_k | \mathbf{H}_k^q)}{d\mathbf{H}_k} = 0$, we get

$$\begin{aligned} h_{1k}^{q+1} &= \frac{1}{N_d} \sum_{n=1}^{N_d} \left(\sum_{\bar{\mathbf{x}}_{2k}} x_{2k}^*(n) y_{2k}(n) \Pr(x_{2k}(n)) \right. \\ &\quad \left. - \sum_{\bar{\mathbf{x}}_{2k+1}} x_{2k+1}(n) y_{2k+1}(n) \Pr(x_{2k+1}(n)) \right) \\ h_{2k}^{q+1} &= \frac{1}{N_d} \sum_{n=1}^{N_d} \left(\sum_{\bar{\mathbf{x}}_{2k}} x_{2k}(n) y_{2k+1}(n) \Pr(x_{2k}(n)) \right. \\ &\quad \left. + \sum_{\bar{\mathbf{x}}_{2k+1}} x_{2k+1}^*(n) y_{2k}(n) \Pr(x_{2k+1}(n)) \right) \end{aligned} \quad (6.34)$$

These two equations represent the solution to the estimation of the channel; this estimate is used in the next iteration. Note that $\Pr(x_{2k}(n))$ and $\Pr(x_{2k+1}(n))$ can be obtained from the data detection module using BCJR algorithm discussed in the next section. The estimated channel is passed to the OSTBC decoder for the subsequent iteration. The proposed channel estimation method entails a low computational complexity since the complexity is proportional to the frame length. The three parts of the proposed receiver shown in Figure 6.1 exchange and update information through iterations. The accuracy of data detection is highly dependent on the accuracy of channel estimation, while channel estimation is expected to have lower error covariance if the APP of transmitted signals provided by the data detection part is more accurate. Through iterations and with a proper initialization, it is expected that both accurate data detection and channel estimation are achieved.

6.5.2 Use of the BCJR Algorithm

In order to use the EM based channel estimation algorithm described in Eq. (6.34), we need to know the APP of transmitted CPM signals. As mentioned earlier, $\Pr(x_k(n))$ is the simplified representation of $\Pr(x_k(n) | x_k(n-1), \dots, x_k(1), \mathbf{Y}_k, \mathbf{H}_k^q)$. It appears that the evaluation of the above quantity is not straightforward. Fortunately, the well known BCJR algorithm can be adopted not only for the evaluation of the APP of the transmitted CPM signals but also for data detection. A state diagram is usually required in the demodulation of CPM signals in which the state at $t = nT$ is the combination of a cumulative state and a correlative state $s_n = \{\theta_n, a_{n-L+1}, \dots, a_n\}$. The evaluation of the term $\Pr(x_k(n) | x_k(n-1), \dots, x_k(1), \mathbf{Y}_k, \mathbf{H}_k^{(q)})$ in Eq. (6.27) can be obtained by the BCJR algorithm which is a computationally efficient algorithm for MAP data detection. A detailed introduction to the BCJR algorithm has been provided in Chapter 1. BCJR algorithm usually provides the soft information about input symbols. Here we also use BCJR algorithm to obtain the soft information about state transitions in every symbol interval. For clarity

and simplicity, we omit the block index k in the following discussion. When the previous input is conditionally known, the starting state s_n is also conditionally known. Thus, we have

$$\Pr(x(n) | x(n-1), \dots, x(1), \mathbf{Y}, \mathbf{H}^{(q)}) = \Pr(s_{n+1} | s_n, \mathbf{Y}, \mathbf{H}^{(q)}). \quad (6.35)$$

Moreover, following [7], we get

$$\Pr(s_{n+1} | s_n, \mathbf{Y}, \mathbf{H}^{(q)}) = \gamma(s_n \rightarrow s_{n+1}) \alpha(s_n) \beta(s_{n+1}), \quad (6.36)$$

where $\gamma(s_n \rightarrow s_{n+1}) = f(s_{n+1}, Y | s_n, \mathbf{H}^{(q)})$, $\alpha(s_n) = f(s_n, \mathbf{Y}_0^n)$ is the forward coefficient and $\beta(s_{n+1}) = f(\mathbf{Y}_n^{N_b} | s_{n+1})$ is the backward coefficient, $\mathbf{Y}_0^n$ and $\mathbf{Y}_n^{N_b}$ are the received signal sequences before and after the n th symbol interval in the same block. The forward evaluation of α and β is based on γ . These two coefficients can be calculated recursively by Eq. (2.31).

For a given start state s_n and end state s_{n+1} , a unique transmitted CPM signal can be specified. If $x(\cdot)$ denotes the corresponding relationship between state transition and CPM signal, the state transition probability during the n th symbol can be expressed as

$$\gamma(s_n \rightarrow s_{n+1}) = \exp\left(\frac{1}{2\sigma^2} |y(n) - h^q(n)x(s_n, s_{n+1})|^2\right). \quad (6.37)$$

Eqs. (6.35) and (6.37) provide the solution to the evaluation of the APP for state transitions which is required in the EM algorithm. In Section 6.4, in order to preserve phase continuity between blocks, the start and end phases for each block must obey the rule in Eqs. (6.15) and (6.16) and their values are constant. Consequently, for the start and end phases which have the same values as in Eqs. (6.15) and (6.16), $\alpha(s_0)$ and $\beta(s_{N_b})$ are given a probability of 1 and, for other phases, a probability of 0 is assigned.

For simplicity, we only consider a binary transmission ($M = 2$) here. After several iterations, the receiver terminates the channel estimation and the evaluation of APP of state

Algorithm 2: Joint Data Detection and Channel Estimation for orthogonal space-time
block coded CPM

```

1 for  $i = 1 : N$  do
2   Channel initialization by pilots;
3   for  $q = 1 : ite$  do
4     if  $\|\mathbf{H}^{(q+1)} - \mathbf{H}^{(q)}\| \leq \varepsilon$  then
5       OSTBC decoding;
6       APP update for state transition by Eq. (6.35);
7       EM channel updating by Eq. (6.34);
8     else
9       OSTBC decoding;
10    APP calculation for input symbols and data decision;

```

transition. The BCJR algorithm uses the estimated channel to compute the probabilities of input symbols as

$$\begin{aligned}
\Pr(a_n = 1 | \mathbf{Y}, \mathbf{H}^{(q)}) &= \sum_{ST_{+1}} \Pr(s_n \rightarrow s_{n+1} | \mathbf{Y}, \mathbf{H}^{(q)}) \\
\Pr(a_n = -1 | \mathbf{Y}, \mathbf{H}^{(q)}) &= \sum_{ST_{-1}} \Pr(s_n \rightarrow s_{n+1} | \mathbf{Y}, \mathbf{H}^{(q)}) \quad , \quad (6.38)
\end{aligned}$$

where ST_{+1} and ST_{-1} represent the state transitions $s_n \rightarrow s_{n+1}$ associated with the input symbol $a_n = 1$ and $a_n = -1$, respectively. The proposed receiver algorithm is summarized in Algorithm 2.

6.6 Simulation Results

In this section, we show some simulation results of the proposed iterative data detection and channel estimation algorithm for orthogonal space-time block coded CPM with two transmit and one receive antennas. We first illustrate the effectiveness of the proposed block construction of Section 6.4 on preserving bandwidth efficiency of orthogonal space-time block coded CPM signals and then we show the performance of the iterative data detection and channel estimation algorithm.

6.6.1 Bandwidth Efficiency of the Proposed Orthogonal Space-Time Block Coded CPM

Figure 6.5: Spectral comparison between space-time block coded full response CPM signal ($M = 2$, $h = 0.25$, rectangular frequency pulse) with and without a tail sequence

To show the effectiveness of the proposed method on spectral efficiency, the power spectra of space-time block coded CPM with and without a tail sequence are compared. A full response CPM signal with rectangular frequency pulse shaping and $h = 0.25$ is considered in Fig. 6.5. In this case two tail symbols for each block are sufficient to ensure phase continuity. In Fig. 6.6, we consider GMSK (Gaussian minimum shift keying) signal with $h = 0.5$, bandwidth $BT = 0.3$ and $L = 4$ which is the adopted scheme in GSM standards. Four tail symbols per block are required to ensure phase continuity. In these two simulations, the block length is 30 symbol intervals and the sampling rate is 8 samples per symbol. The power spectra are calculated by averaging the squared magnitude of the FFTs of 10^3 different discrete time segments. Each segment comprises 10^4 data symbols.

Figure 6.6: Spectral comparison between space-time block coded GMSK ($L = 4$, $h = 0.5$, $BT = 0.3$) with and without a tail sequence

The frequency is normalized with the bit rate $1/T_b$ where T_b is the bit duration. The peak value of power spectra is normalized to 0dB for a fair comparison. Fig. 6.5 and 6.6 show that inserting tail sequence maintains the spectral efficiency of CPM, whereas, ignoring the phase continuity between consecutive block will lead to a loss in spectral efficiency.

6.6.2 Performance of the Proposed Iterative Algorithm

In the following simulations, the Jake's model is used to approximate block fading channel. Its autocorrelation function is give by $R[n] = J_0(2\pi f_d T n)$ where $J_0(\cdot)$ is the zeroth order Bessel function of the first kind and $f_d T$ is the normalized Doppler frequency. The proposed receiver processes a packet which consists of five blocks and only the first two symbols of the first block in every packet are assigned to pilots. Initialization for the blocks which does not contain pilots ahead is evaluated by the prediction of the estimated channel of the previous block. Within each iteration, the receiver processes 10^6 packets (each

Figure 6.7: BER performance provided by the proposed algorithms for $f_d T = 0.02$

Figure 6.8: BER performance provided by the proposed algorithms for $f_d T = 0.05$.

Figure 6.9: MSE of channel estimation versus E_b/N_0 for different numbers of iterations

packet contains 150 symbols). For simplicity, MSK is considered here. Fig. 6.7 and Fig. 6.8 show the bit error rate (BER) produced by the proposed iterative receiver for different number of iterations when the block fading rates are $f_d T = 0.02$ and $f_d T = 0.05$ respectively. The performance with the availability of perfect channel state information is also included in these figures for comparison. Note that the notation *Iterations* = i refers to the performance after i th iterations of the EM algorithm. Several conclusions can be made from Figs. 6.7 and 6.8. Through iterations, the performance is significantly improved and the largest performance improvement is achieved between the first and the second iteration. When $f_d T = 0.02$, the proposed scheme approaches the optimum performance after the third EM iteration. When the number of iterations is larger than two, the performance improvement brought by further iterations is negligible. Thus we conclude that a small number of iterations can achieve accurate channel estimation.

The mean square error (MSE) of channel estimation for different number of iterations

Figure 6.10: Comparison among three kinds of channel estimation methods

is shown in Fig. 6.9. The setting of this simulation is same as that used in Fig. 6.7. In the first iteration, the channel is initialized by two pilot symbols per five blocks. Since the rate of pilot insertions and the length of the pilot sequence is small, the MSEs correspond to the first iteration are relatively high. There exists a large gap between MSEs of the first iteration and the second iteration. The MSEs improvement from the second iteration to the third iteration is much less than the initial improvement. Since the demodulator and channel estimation interact with each other, the behavior of the MSE improvement versus the number of iterations in Fig. 6.9 is the same as the BER improvement evidenced by Fig. 6.7.

6.6.3 Comparison with Other Algorithms

In the iterative receiver, the proposed EM based channel estimator may be replaced by other channel estimators, such as Kalman smoothing [101] and pilot only method. Kalman

smoothing consists of a forward recursion followed by a backward recursion. Pilot only method uses the channel estimates by means of pilot only and there is no channel updating between blocks. Here the performance of the receivers with these three different channel estimators are compared in terms of BER values, as shown in Fig. 6.10. $f_d T = 0.02$ is used in the simulation and other parameters are the same as in Fig. 6.7. The curves of the proposed method and the Kalman smoothing are obtained after the third iteration. As can be seen, the proposed method provides the best performance and approaches the performance endowed with known channel state information. This is mainly due to the use of soft information by the EM channel estimator.

6.7 Summary

Due to sign change and phase conjugation as required by OSTBC, the direct combination of an OSTBC with CPM will disrupt the phase continuity between consecutive blocks. In this chapter we first propose a novel block construction using a tail sequence to guarantee the phase continuity between blocks for all antennas so that the attractive properties of CPM waveforms can be preserved. We had shown that the proposed construction method guarantees high throughput and that the evaluation of the tail sequence can be carried out at only one antenna. Simulation results show that the proposed scheme improves the bandwidth efficiency at an acceptable cost of data throughput. At the receiver, a method is proposed to solve the problem of joint data detection and channel estimation. It had been shown that, through iterations, the proposed method approaches optimal performance with known channel information even when channel variations are significant.

Chapter 7

Conclusions and Future Work

7.1 Conclusions

Wireless communications call for high data rate, bandwidth efficient transmissions. Due to its properties of bandwidth and power efficiency, CPM is a suitable candidate for wireless communication. One of the frequently occurring problems in wireless communications is the presence of time-varying flat fading channels which generate a multiplicative distortion to the transmitted signals. Especially, accurate data detection becomes more difficult when channel goes through deep fading. The combination of convolutional coding and orthogonal space-time block coding with CPM provides performance gain compared with the uncoded CPM signals. However, these systems typically operate at a low SNR and, therefore, reliable channel estimation is challenging. In this thesis various enhanced algorithms have been proposed to solve the problem of joint data detection and channel estimation for uncoded and coded CPM signals transmitted over AWGN and fading channels. The proposed algorithms have been analyzed in details and compared with other methods available in the literature.

First, the problem of the demodulation of a CPM signal over an AWGN channel was addressed. The existing algorithms need to incorporate an additional procedure for modulation index and alphabet size estimation. Furthermore, a small estimation error in the modulation index has a large impact on the performance of CPM demodulation. We proposed

a frequency and phase estimation based demodulation method which does not require the recovery of modulation index and alphabet size. Simulation results show that the proposed method lose 0.5 dB in performance compared to the VA endowed with the known modulation index and the alphabet size. However, the frequency and phase estimation involved in the proposed method makes its computational complexity higher than the complexity of the conventional VA, if the size of the trellis is small.

Secondly, the problem of joint data detection and channel estimation for uncoded CPM signals in time-varying fading channels was addressed. A forward channel prediction over a given observation interval is obtained via Kalman prediction. Then a decision is taken on the first symbol of the observation interval in VA. After that the detected symbol is fed back for channel updating and state updating for the next symbol detection. These steps are repeated until the end of the received sequence. The prediction over a given interval guarantees zero decision delay and, at the same time, maintains the accuracy of the survivor path selection. Therefore, the proposed method is expected to provide better performance than the PSP and SEP methods and this is confirmed by computer simulations. The required calculation number in the proposed algorithm is roughly L_o times larger than the PSP and SEP algorithms where L_o is the observation interval.

Thirdly, we had extended the method proposed for uncoded CPM signals (which can only produce hard outputs) to a novel adaptive SISO module that addresses the problem of joint data detection and channel estimation for SCCPM signals transmitted over a time-varying flat fading channel. The proposed SISO module consists mainly of two parts: a truncated BCJR algorithm and a channel tracker using KF. These two parts exchange and update information in every symbol interval. Due to its ability of incorporating the a priori symbol probabilities and its use of soft outputs, the proposed SISO module is well suited for an iterative receiver such as a receiver developed for turbo codes. The convergence behavior and the effects of interleaver size have also been analyzed. BER comparisons with existing algorithms have been presented to show the efficacy of the proposed algorithm.

Fourthly, to allow the use of OSTBCs, we had proposed a method to ensure phase continuity at the transmitter. Due to the requirement of phase continuity and the associated memory of CPM, the combination of an OSTBC with CPM is not as straightforward as with linear modulation schemes. To ensure phase continuity, a tail sequence at the end of each block is inserted so that the end phase of every block satisfies certain restrictions. We have shown that the proposed construction results in a high throughput and that the evaluation of the tail sequence can be carried out at only one antenna. Simulation results show that the proposed block construction entails a negligible loss in data throughput.

Finally, the EM algorithm had been applied to channel estimation of the space-time block coded CPM signals under the assumption of a quasi-static channel. The estimated channel information has been used for the evaluation of APP of transmitted CPM signals in the data detection part. These two steps run iteratively. Initial channel estimates are obtained using a small number of pilots in order to prevent the divergence of channel tracking. It has been shown that, after several iterations, the proposed method can approach the performance achieved in the presence of known channel state information even when the fading rate is high. Simulation results also show that the proposed method obviously outperforms the classical ‘Pilot’ and ‘DDKF’ methods. Since the proposed algorithm operates in an iterative manner, the performance gain is at the sacrifice of computational complexity.

7.2 Future Work

In this section, some topics that may deserve further investigation are listed.

In Chapters 4 and 5 hard output and soft output demodulators for uncoded and serially concatenated CPM signals were proposed. However, bounds on their error performance were not provided. If such bounds were derived, the performance could be predicted.

When designing a communication system, its computational complexity is always an important issue which needs to be carefully considered. We have adopted the truncated

Viterbi and BCJR algorithms for data detection in Chapters 4 and 5, respectively. There exists a large amount of work in the literature on the complexity reduction of Viterbi and BCJR algorithms and these could be used to reduce the complexity of the receivers proposed in the thesis.

In the case of space-time block coded CPM signals, we have only considered one receiver antenna and the soft information provided by the data detector was used in the procedure of channel estimation. When considering multiple receiver antennas, soft information could be also useful for antenna selection. In this thesis, we have considered convolutional encoded CPM and space-time block coded CPM in Chapters 5 and 6, respectively. The convolutional encoded CPM introduced in Chapter 5 achieves coding gain, whereas the space-time block coded CPM introduced in Chapter 6 achieves diversity gain. The space-time trellis coded CPM is a combination of a convolutional code and a STBC; therefore it will attain coding and diversity gain at the same time. The methods proposed in this thesis could be extended to space-time trellis coded CPM formats.

Throughout the thesis, we have considered frequency flat fading channel only. It is possible to extend the proposed approaches to time-varying multi-path channel. In the literature, multi-path channels are often assumed to be quasi-static. The tracking techniques introduced in this thesis are also suitable for developing efficient CPM detection algorithms for time-varying multi-path channels.

Publications

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- W. Wang and S. S. Abeysekera, “Decision directed data detection and channel estimation for CPM in frequency-flat fading channel,” accepted by *Wireless Communications and Mobile Computing*.
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