Reduced-Complexity Equalization for EDGE

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UniS

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Abstract

Enhanced Data Rates for GSM Evolution (EDGE) is currently being standardized as the evolution path for GSM. EDGE improves the spectral efficiency by employing an 8PSK modulation scheme with $\frac{3\pi}{8}$ rotation between symbols, which triples the GSM data rate. A Linearized-GMSK pulse shaping filter is employed to remain within the 200kHz bandwidth of GSM. In order to facilitate the ease of transition from GSM to EDGE, system parameters such as symbol rate and time slot structure remain unchanged. As a result, a network capable of EDGE can be deployed with limited investment and within a short time frame, with just an upgrade in the transceiver and the system software.

The introduction of EDGE modulation has a significant effect in the receiver. The LGMSK filter introduces Inter-symbol interference whose effect becomes severe due to multi-path fading and Doppler Spreading. In addition, 8-PSK has a smaller Euclidean distance between symbols than GMSK, which makes EDGE more prone to errors. Therefore a robust equalizer is required.

The research objective is to mitigate the effects of fast time-varying frequency selective fading channels in the presence of noise and interference, by optimizing the trade-off between complexity and performance. This leads to four main areas of study: Reduced-state Equalization, Pre-filtering, Reduced-state Soft Output Equalization and Joint Pre-filter, Channel and Reduced State Soft Output Data Estimation.

The optimum scheme, Maximum Likelihood Sequence Estimation, based on the Viterbi Algorithm, for a 6-tap channel requires 32768 $(8^5)$ trellis states. Using the techniques developed in this thesis, an implementation margin of 5.9 dB over the EDGE standard requirement is achieved with only a 2 trellis state equalizer. Subsequently, based on this low complexity structure, a new method is developed involving two stages of equalizers in cascade. With reduced decision errors and improved noise variance estimation, the two stage scheme leads to a performance surpassing the single stage, with good resistance to interference. Finally, a joint scheme of moderate complexity is developed to support the scenario of a high speed train.

Key words: EDGE, GSM, Equalization, DDFSE, RSSE, MAP, SSA
Acknowledgements

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Last but not least, my special thanks goes to my family for the patience and my wife for the moral support throughout the course.
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Chapter 1

Introduction

1.1 GSM Evolution towards 3G

The Third Generation (3G) mobile communication systems are currently in the standardization phase. Two major technologies have been defined. Firstly, the introduction of completely new radio access schemes, such as the Universal Mobile Telecommunication System (UMTS), which is based on Wideband Code Division Multiple Access (WCDMA). The other solution known as EDGE is based on the evolution of the existing Time Division Multiple Access (TDMA) systems - GSM and IS-136, which are Second Generation (2G) cellular standards with worldwide success.

Although speech is still the main service of these new mobile systems, the support for data communications over the air interface is greatly improved. The current GSM standard provides data services with user bit rates up to 14.4kbps for Circuit Switched Data (CSD) and up to 22.8kbps for packet data. Higher bit rates can be achieved with multi-slot operation and this adds two new services to the radio interface known as the High Speed Circuit Switched Data (HSCSD) and the General Packet Radio Service (GPRS), which allow users to remain connected to the network but only use the radio capacity when actually transmitting or receiving data. However, these techniques are based on the Gaussian Minimum Shift Keying (GMSK) modulation scheme and they yield only a moderate increase in the bit rates per time slot. The objective of EDGE is to increase data transmission rates and spectrum efficiency so as to facilitate new
1.2 An Overview of EDGE

applications and increase capacity for mobile use. It also enhances the existing services to meet the basic requirements in 3G.

EDGE can be introduced in two ways: as a packet-switched enhancement known as the Enhanced General Packet Radio Service (EGPRS) and as a circuit-switched data enhancement called Enhanced Circuit Switched Data (ECSD). A new modulation technique and error-tolerant transmission methods, combined with improved link adaptation mechanisms make these EGPRS rates possible. This is the key to increased spectrum efficiency and enhanced applications, such as wireless Internet access, e-mail and file transfer. In addition to enhancing the throughput per data user, EDGE also increases capacity. With EDGE, the same time slot can now support more users. This decreases the number of radio resources required to support the same traffic, thus freeing up capacity for more data or voice users. It also allows circuit-switched and packet switched traffic to coexist while making more efficient use of the same radio resources and thus boosting the capacity for the data traffic.

Based on EDGE high-speed transmission techniques combined with EGPRS, EDGE provides the ability to align with UMTS, further evolving GSM towards the 3G wireless systems and results in the standard known as GSM/EDGE Radio Access Network (GERAN). This allows conversational and streaming service classes that are defined for WCDMA to be supported by EDGE. By doing so, a new range of applications, including Internet Protocol (IP) multimedia applications can be adequately supported [1]. The drive for such evolution is the paradigm shift within the telecommunications world from circuit to packet switched communications. This trend is occurring for not only traditional data services such as email and web browsing but also for real-time services such as video-conferencing and voice over IP.

1.2 An Overview of EDGE

Modulation Technique

In EDGE the gross data bit rate on the air interface is increased with the introduction of 8-PSK at the same symbol rate of 270.833kHz as in GSM. In order to fit within
1.2. An Overview of EDGE

<table>
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<tr>
<th>System Parameters</th>
<th>GSM</th>
<th>EDGE</th>
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<tr>
<td>Modulation</td>
<td>GMSK</td>
<td>8-PSK, GMSK</td>
</tr>
<tr>
<td>Spectrum Efficiency</td>
<td>1 bit/symbol</td>
<td>3 bit/symbol</td>
</tr>
<tr>
<td>Filter</td>
<td>0.3-Gaussian</td>
<td>0.3-LGMSK</td>
</tr>
<tr>
<td>Modulation Bit rate</td>
<td>270kbps</td>
<td>810kbps</td>
</tr>
<tr>
<td>Radio data rate per time slot</td>
<td>22.8kbps</td>
<td>69.2kbps</td>
</tr>
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Table 1.1: Overview of GSM and EDGE System Parameter

the 200kHz bandwidth and to reduce the peak-to-average power ratio at the input of the power amplifier a LGMSK filter is used. This results in the same adjacent channel interference as in normal GSM, which allows the EDGE channels to be integrated into the existing frequency plan. A modulation technique similar to π/4-DQPSK is introduced in EDGE resulting in the 3π/8 rotated 8-PSK constellation as shown in figure 1.4. The signal trajectory avoids crossing the origin of the constellation and hence it can tolerate non-linear power amplifiers. With this modulation technique, a gross bit rate of 69.2kbps per time slot (compared with current 22.8kbps) is achieved while still fulfilling the GSM spectrum masks and leaving the burst duration unchanged as shown in figure 1.1.

Coding Schemes

Four different Coding Schemes (CS), designated CS-1 to CS-4 [2] based on the GSM GMSK modulation scheme are defined for the GPRS. Each has different amounts of error-correcting coding that is optimised for different radio environments. EDGE uses nine different Modulation and Coding Schemes (MCS) to support packet data communications under different channel conditions [2]. They fulfil the same objectives as the GPRS coding schemes. The lower four of EGPRS coding schemes (MCS-1 to MCS-4) uses the GMSK modulation while the upper five (MCS-5 to MCS-9) use the 8PSK modulation as shown in figure 1.2. The incoming data bits are delivered in 20ms blocks and are encoded using a rate \( \frac{1}{2} \) convolutional code of constraint length 7. The coded bit stream is punctured to the required code rate corresponding to the modulation coding scheme as shown in figure 1.2. Subsequently, the encoded bits are interleaved
1.2. An Overview of EDGE Coding Scheme

<table>
<thead>
<tr>
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<th>Modulation</th>
<th>Code Rate</th>
<th>RLC Payload [bits]</th>
<th>Max. Data Rate [kbps]</th>
<th>Blocks per 20ms</th>
<th>Family</th>
<th>IR sub-blocks</th>
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<td>MCS-1</td>
<td>G</td>
<td>0.53</td>
<td>176</td>
<td>8.8</td>
<td>1</td>
<td>C</td>
<td>2</td>
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<tr>
<td>MCS-2</td>
<td>M</td>
<td>0.66</td>
<td>224</td>
<td>11.2</td>
<td>1</td>
<td>B</td>
<td>2</td>
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<tr>
<td>MCS-3</td>
<td>S</td>
<td>0.85</td>
<td>296</td>
<td>14.8</td>
<td>1</td>
<td>A</td>
<td>3</td>
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<tr>
<td>MCS-4</td>
<td>K</td>
<td>1.00</td>
<td>352</td>
<td>17.6</td>
<td>1</td>
<td>C</td>
<td>3</td>
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<tr>
<td>MCS-5</td>
<td>B</td>
<td>0.37</td>
<td>448</td>
<td>22.4</td>
<td>1</td>
<td>B</td>
<td>2</td>
</tr>
<tr>
<td>MCS-6</td>
<td></td>
<td>0.49</td>
<td>592</td>
<td>29.6</td>
<td>1</td>
<td>A</td>
<td>2</td>
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<tr>
<td>MCS-7</td>
<td>P</td>
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<td>896</td>
<td>44.8</td>
<td>2</td>
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<td>MCS-8</td>
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<td>0.92</td>
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<td>54.2</td>
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<td>A</td>
<td>3</td>
</tr>
<tr>
<td>MCS-9</td>
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<td>1.00</td>
<td>1088</td>
<td>59.2</td>
<td>2</td>
<td>A</td>
<td>3</td>
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Table 1.2: Overview of EDGE Modulation Coding Schemes

for protection against fading. According to the standard the EGPRS is capable of a bit rate up to 59.2kbps [3] with increasing radio quality. The GPRS throughput reaches saturation at a maximum of 21.4kbps with CS-4 [2].

Packet Handling

Several channel coding schemes have been defined to ensure robustness in a variety of channel conditions. A technique known as Link Adaptation (LA) provides the dynamic switching between coding and modulation schemes. A packet sent with a higher coding scheme (less error correction) that is not properly received can be retransmitted with a lower coding scheme if the new radio environment becomes undesirable. This process is known as re-segmentation [4] where re-transmission initiates another coding scheme to suit the changing environment. This requires changes in the payload size of the radio block and accounts for the difference in performance between EGPRS and GPRS. However, re-segmentation is not possible with GPRS and requires careful selection of the coding scheme in order to avoid frequent retransmissions and is therefore not desirable in a rapidly changing environment. However with EGPRS the impact of a
changing environment is smaller as re-segmentation is possible.

Interleaving

The interleaving procedure has been changed within the EGPRS standard so as to increase the performance of the higher coding schemes such as MCS-7 to MCS-9. When Frequency Hopping (FH) is used, the radio environment is changing on a per-burst level. Due to the fact that a radio block is interleaved and transmitted over four bursts for GPRS, each burst may experience a completely different interference environment. If one of the 4 bursts is not properly received, it will require a re-transmission [5]. In the case of CS-4 for GPRS, hardly any error protection is used. With EGPRS, the higher coding scheme are handled differently to resolve the problem faced by GPRS. The MCS-7 to 9 schemes actually transmit 2 radio blocks over the four bursts and interleaving occurs over two bursts instead of four [4]. This reduces the number of bursts that must be transmitted should errors occur as shown in Figure 1.1. The likelihood of receiving two consecutive error free bursts is higher than receiving four consecutive error free bursts. This implies that the higher coding schemes for EDGE have a better robustness with regard to FH.

![Interleaving Diagram](image)

Figure 1.1: Interleaving

Link Adaptation and Incremental redundancy

EGPRS uses a combination of LA and Incremental Redundancy (IR) to achieve the highest possible throughput over the radio link. Link adaptation uses the radio link quality, measured either by the Mobile Station (MS) in a downlink transfer or by Base Station (BS) in the uplink transfer to select the most appropriate modulation coding
scheme for the transmission of the next sequence of packets. For an uplink packet transfer, the network informs the MS which coding scheme to use for transmission for the next sequence of packets. The modulation coding scheme can be changed for each radio block (four burst) but each change is initiated with a new set of quality estimates. There are three families as shown in figure 1.2. Within each family, there is relationship between the payload sizes, which makes re-segmentation for re-transmission possible as shown in figure 1.2. IR initially uses a coding scheme such as MCS-9 with very little protection and without consideration for the actual radio link quality. When information is received incorrectly, additional coding is transmitted and then soft combined in the receiver with the previously received information. The soft-combining [6] increases the probability of decoding the information. This procedure will be repeated until the information is successfully decoded. This implies that knowledge about the radio link is not necessary, which is a desirable feature and suitable for the MS. In fact, IR is a mandatory standard in mobile stations [4]. As an example, the whole of the Radio Link Control (RLC) block is convolutionally encoded with rate 1/3. A maximum of three different puncturing scheme derived 3 sub-blocks: P1 - P3 [7], as shown in Figure

![Figure 1.2: Link Adaptation - Packet Resegmentation](image-url)
1.3. Problem Definition

1.3. For initial transmission any modulation coding scheme can be selected based on the current link quality. First P1 is transmitted; if it cannot be decoded, P2 and P3 are subsequently sent until the receiver can successfully decode the RLC block via soft combining [6] of all received blocks. As a result, the code rate is dynamically adjusted according to the experienced radio condition without using explicit measurements.

![Diagram](https://via.placeholder.com/150)

Figure 1.3: Coding and Puncturing for MCS-8, Code rate 0.92, 2 RLC blocks per 20ms

### 1.3 Problem Definition

EDGE induced modifications to the air interface have a direct impact on the link robustness and the design of the transceivers even though various system parameters such as the symbol rate, burst duration and channel bandwidth remains unchanged. Although LA is being introduced to improve the robustness of the link, the problems in the system design of the transceiver should not be underestimated. In fact, the design of the equalizer block has the greatest impact on the overall performance of the system [8] and therefore channel equalization is the main focus of the thesis.

The introduction of the 8-PSK modulation results in a shorter Euclidean distance between each transmitted symbol as compared to the GMSK in GSM and thus EDGE
1.3. Problem Definition

systems are more prone to errors. In addition, the LGMSK pulse shape filter introduces ISI and the effects become more severe due to multi-path fading and Doppler spreading. The effects of pulse shaping can be seen in fig.1.4. Severe ISI is being introduced even without Additive White Gaussian Noise (AWGN) as the trajectories 'blurred' the constellation points.

![Figure 1.4: $\frac{3\pi}{8}$-Offset 8PSK Trajectories](image)

The optimum equalizer structure based on the VA or MLSE provides the optimum solution and is implemented in GSM but becomes too complex [9] for practical implementation with currently available DSPs in EDGE.

The main limitation of Viterbi Equalizers (VE) is that the number of trellis states required to perform sequence estimation increases exponentially with the symbol alphabet size and the length of channel memory. For example in EDGE 8^6 or 32768 trellis states are required for optimum equalization over a six tap channel. Sub-optimum techniques are therefore necessary as an implied requirement in a low cost transceiver. This is a highly desirable feature for a mobile handset where power and processing is limited.

The natural method of reducing the complexity in MLSE is to prune the size of the
1.3. Problem Definition

trellis. However reduced complexity schemes such as reduced state (DDFSE, RSSE) and even reduced search (M-algorithm) are sensitive to the phase of the Overall Channel Impulse Response (OCIR) [8]. Good performance can only be achieved provided that the OCIR (including pulse shaping filter, channel and receive filter) is minimum phase, and this requires a pre-filter to be inserted prior to the equalizer [8]. This is because reduced state schemes like the DDFSE and RSSE utilize only the first $\mu + 1$ taps of the OCIR in the definition of the trellis and therefore require the OCIR's tap energy to be concentrated near the zero time delay. The Training Sequence (TS) in EDGE that provides a known start state to the trellis equalizer is located at the centre of the time slot. This suggests that equalization has to be carried out bi-directionally starting from the centre towards the start and end of the time slot. As the backward equalization proceeds in the negative time direction (end to centre of burst) it now requires a maximum phase OCIR as shown in figure 1.5 and therefore two pre-filtering operations are needed for each time slot. In addition, the computation of the pre-filter itself is a substantially complex process [8].

![Figure 1.5: Bi-directional Equalization and Channel Impulse Response Transformation](image)

In a mobile communication environment, the channel is time-varying and unknown a priori. At high vehicular speeds the performance could degrade dramatically causing a high irreducible error floor in the Bit Error Rate (BER) performance. The OCIR is estimated with the aid of TS and is only accurate at the centre of the time slot. In
reality, the OCIR can vary significantly towards each end of the time slot and hence channel derived parameters such as the pre-filter would result in an 'average' unless tracking is employed. In situations like high speed trains, adaptive methods become necessary but require computationally intensive tracking algorithms. In EDGE the services are expected to be used by quasi-stationary users, which implies that high mobile velocities are unlikely. For fast channel dynamics GMSK modulation can be used but at much lower data rates.

In addition to multi-path fading and noise, resistance to interference is in fact the most important issue to be dealt with, as it is the limiting factor to the system capacity. Due to the limited bandwidth availability, channel spacing is minimized to accommodate more carriers. The spectral overlap between neighbouring channels signals results in Adjacent Channel Interference (ACI) that degrades receiver performance depending on the signal design parameters such as bandwidth and modulation. In EDGE or GSM, the carriers are carefully constrained by the LGMSK to 200kHz spacing. Assuming the given carrier spacing the Co-Channel Interference (CCI) is the next limiting factor in the system capacity. Cellular systems exploit the concept of frequency reuse, meaning that the same frequencies are repeated according to a certain reuse pattern or distance as shown (in figure 3.10) to achieve the required capacity. Frequency re-use causes inherent CCI problems in receivers. Hence the reuse pattern cannot be reduced without loss in the quality of service. However, CCI can be suppressed using interference cancellation [10] and interference rejection techniques [11,12] but at a cost of substantial complexity, the additional processing for which is not easily available in the case in mobile handsets. Evidently, cellular capacity can be improved if a receiver susceptibility to the interference can be reduced. In EDGE, five MCS modes have been defined for EGPRS and therefore the concatenation of the equalizer and the channel decoder provides a powerful means for improving the receiver performance. The performance degradation due to interference can be further minimised by improving the reliability of the detection scheme, where soft decisions can be exploited from the coding schemes using soft-output algorithms. Depending on the type of soft-output algorithms, they can result in high implementation complexity. The BCJR Maximum A Posteriori (MAP) algorithms are optimal in estimating the soft bit values but incur high complexity in
1.4. Research Objectives

The main motivation of this research is to mitigate the effect of fast time-varying frequency selective fading in presence of noise and interference for EDGE. Due to the high complexity required by MLSE, a low complexity trellis type equalizer design with approximate performance to the MLSE is desirable. Reducing the complexity while maintaining the required performance remains the priority of a trellis based equalizer system. The tradeoff between complexity and performance is unavoidable as each impairment requires a corresponding mitigation process. This incurs additional complexity. The aim is to seek for an sub-optimum solution that is a compromise. A low complexity equalizer also implies a low cost transceiver which is an advantage for handsets. Thus the purpose of this research is to determine a suitable practical solution with specific interest in high data rate services - EGPRS which is capable of bit rates up to 59.2kbps per time slot. This leads to 4 main areas of study:

Reduced State Equalizers The first step is to determine the lowest possible number of trellis states that is capable of giving useful equalization performance in EDGE.

Pre-filtering The design of the pre-filter is investigated as it has a direct impact on the complexity of the overall equalization scheme, which includes itself and the trellis equalizer. As the pre-filter computation is complex, an efficient design is required.
1.5 Thesis Overview

**Soft-output Equalizers** The study looks into the design of reduced state soft-output algorithms that have strong resistance to interference. For MAP, the effects of logarithmic simplifications and reduced state are investigated over the GSM channel profile. The investigation also extends to sub-optimum methods like the SSA.

**Joint Channel and Data Estimation** The study looks into a low complexity adaptive soft-output algorithm to mitigate the effects of fast time-varying frequency selective fading. Channels with fast dynamics, such as the case of a high speed trains is investigated.

The thesis investigates the four research objectives with the aim to define and formulate a practical and low complexity equalizer that is suitable for EDGE.

1.5 Thesis Overview

The overview of the thesis is illustrated in figure 1.6. This chapter (chapter 1) provides an overview of the GSM and EDGE communication systems. The problems regarding the optimum equalization and sub-optimum schemes in terms of complexity and robustness are discussed. It also presents the objectives of this research work and lastly the original achievements of this thesis.

Chapter 2 provides a review of the various types of equalization techniques. A summary of current work undertaken in this research area is then presented.

Chapter 3 describes the channel and system simulation models. An outline of channel estimation based on Least Square (LS) approach as adopted in the current work is presented.

Chapter 4 looks into the basic design of a reduced complexity equalizer that involves the DDFSE and a pre-filter. The possibility of further reducing the complexity using set-partitioning is investigated. An efficient pre-filter design based on the idea in [15] is demonstrated. Performance evaluation of the DDFSE, RSSE and pre-filter over the GSM channel is also presented to justify its use.

Chapter 5 applies soft-output algorithms to reduced complexity equalizer structures from chapter 4 and results in the Soft-output DDFSE (SO-DDFSE), Soft-output RSSE
1.6 List of Contributions

The list of original work presented in this thesis is:

i) It is shown in [9,16] that a 8 state DDFSE equalizer is sufficient for equalization in EDGE, the current work first shows the possibility of using the set partitioning to further reduce the complexity of the DDFSE to 4 and 2 state RSSE in [17,18]. In chapter 4, the 2 state RSSE is shown to have similar performance as the 8 state DDFSE, which is later confirmed by [19] with theoretical analysis. As a result a series of low complexity equalizers involving the RSSE is developed for EDGE. The number of states required by the optimum scheme for a 6 tap GSM channel is reduced from 32768 to 2 using the proposed scheme with an approximated performance.

ii) A pre-filter scheme involving Linear Prediction (LP) is developed, which attempts to approximate the Whitening Filter (WF) from the Prediction Error Filter (SO-RSSE) and Reduced-state SSA (RS-SSA). Finally, an improved method that involves the RSSE and Log-MAP in cascade is proposed to reduce the decision errors caused by decision feedback and to improve the noise variance estimation by averaging over the data samples.

Chapter 6 investigates the performance of soft-output equalizer algorithms under rapid channel dynamic conditions such as the situation of a high speed train. Initially, a joint pre-filter, channel and data estimation scheme involving the DDFSE and RSSE from chapter 4 is formulated. The LMS algorithm is used to track the channel dynamics on a per survivor basis. Subsequently, the MAP variants and SSA are applied and result in adaptive soft output algorithms of variable complexity. An analysis of the complexity required by the proposed schemes are also given.

Finally in chapter 7, the main contributions and achievements of the thesis are summarized and conclusions are drawn. Areas in which future research could be carried out are proposed in this chapter.
1.6. List of Contributions

(PEF) [20] using LP. Although a similar technique is shown in [8], it employs the Levinson-Durbin (LD) algorithm to compute the WF coefficients with moderate complexity. However, the current work proposes a much more efficient method that involves the SA. Parallelism is exploited to compute the pre-filter coefficients.

iii) The first reduced state soft output algorithm for EDGE is shown in [21], which involves the DDFSE and Lee's algorithm [22]. Although the approach requires only forward recursion as shown in (appendix C) to deliver the soft decision, it has the disadvantage that its operations are performed in the probability domain. Also, its soft output in (B.8) requires a divide operation, which requires more computational effort than a multiply operation and is therefore not desirable. In order to avoid the disadvantages, the reduced state BCJR Log-MAP is developed in the current work. Both the Log-MAP and Max-Log-MAP variants are considered. In addition, by applying set partitioning, a series of reduced state BCJR based on DDFSE and RSSE are developed as 8 state SO-DDFSE, 4 and 2 state SO-RSSE, and are shown to be possible candidates for reduced complexity equalization in EDGE. Although the 2 state Max-Log-MAP is also shown in [19] as a possible reduced complexity equalizer for EDGE, the current work addresses in detail the effects of reduced state on the performance of BCJR MAP. In addition to BCJR MAP, a much simpler approach that involves the SSA is also introduced. Decision feedback technique in DDFSE is applied to SSA and results in the 8 state RS-SSA, which offers another possible option for reduced complexity equalization in EDGE. The proposed algorithms are extensively evaluated under interference limited channels to determine their resistance to CCI. Finally, a two stage scheme, involving the RSSE and Log-MAP in cascade, is developed as an improvement to the SO-DDFSE, SO-RSSE and RS-SSA. The two stage method reduces the decision errors and provides better noise variance estimates, which results in the cascaded SO-RSSE (CSO-RSSE). It is shown to have a superior performance than the single stage approach, over the GSM channels and most important of all, it is more resistant to interference than the single stage approach. Although, Zeng et al [23] proposed a similar cascaded method as an improvement to the single
stage technique by [21], they employed the DDFSE in cascade with Lee's algorithm and assumed a slow time-varying channel. The current method, employs a RSSE in cascade with a Log-MAP, which has a lower complexity than [23] as Log-MAP simplication and set partitioning is utilized. In addition, the effects of fast time-varying channels are also investigated.

iv) A joint channel, data estimation scheme is adopted as the strategy to combat the fast time-varying ISI. Although there are various similar joint schemes being used for equalization in GSM [24–27], they all involve the MLSE algorithm. A joint RSSE of the channel and data using the PSP and LMS is proposed for tracking fast time-varying channels in EDGE. This scheme is applied to the various proposed soft-output algorithms to cope with rapid channel dynamics. This results in adaptive 8, 4 and 2 states SO-RSSE and RS-SSA. The SO-RSSE and RS-SSA is shown to have performance tightly coupled to complexity, the current work proposed an improved method that implements a low complexity 2 state RSSE joint scheme in cascade with the succeeding Log-MAP. The method reduces the decision errors and provides better noise variance estimates, which results in the Adaptive CSO-RSSE, that is shown to have a superior performance than the single stage approach over the GSM channels.

1.7 Summary

This introductory chapter has briefly overviewed the system aspects of the EDGE system and standard. It has introduced and discussed the nature of the problems of trellis based equalizers in EDGE. The main contributions and the structure of the thesis have been presented.
1.7. Summary

Figure 1.6: Thesis Overview
Chapter 2

Equalization for Wireless Communications

2.1 Introduction

This chapter reviews the various types of equalization techniques ranging from the traditional linear schemes such as the zero-forcing equalizer to the optimum scheme that involves sequence estimation [28]. Recent developments that involve reducing the complexity of the MLSE and various adaptive equalization techniques are reviewed as well as the pre-filtering techniques which are essential in reduced complexity equalization. A survey of a number of soft output algorithms are also presented and finally a summary of the work undertaken for this research project is presented.

2.2 Equalization Techniques

The objective of a detection algorithm in a receiver is to produce a reliable decision of the input sequence given the received data. However, in a multi-path fading channel, the received data can be severely distorted, resulting in errors. Frequency selective distortion is a very common problem in TDMA systems like EDGE. Equalization can compensate for the channel induced ISI that is seen in frequency selective fading. Approaches to data detection can be divided into either symbol by symbol or sequence
2.2. Equalization Techniques

detection [28]. The first class contains linear and non-linear decision feedback detectors. These schemes have lower complexity compared to MLSE but high error rates due to error propagation. Figure 2.1 shows an overview of the various techniques.

---

Symbol-by-Symbol Equalizers

Lucky [29, 30] pioneered the development of an adaptive equalizer for digital communication systems in the mid-1960s. This linear equalizer (LE) is also known as the zero-forcing equalizer (ZFE). The tap values are selected according to the zero-forcing criterion where the ISI is forced to zero. It 'equalizes' the effects of the channel on the frequency response by amplifying the attenuated sections of the frequency response. This can be perceived as an inverse filter, which inverts the folded frequency response of the channel. As a result, this causes excessive noise amplification especially when the channel is in deep fade.

Proakis and Miller [31], Lucky et. al [32] and Gersho [33] developed the linear equalizers based on the Minimum Mean Square Error (MMSE) criterion instead. The tap weights are adjusted to minimize the Mean Square Error (MSE) between the original data symbol and the output of the equalizer, in which the error includes both the ISI as well as the additive noise. As a result, the ISI is not completely removed and does not enhance the noise to the same extent as the ZFE. This results in a lower effective noise
2.2. Equalization Techniques

(ISI and thermal noise) and better BER performance than ZFE, particularly at lower SNR. At high SNR, the MMSE-LE approaches the ZFE-LE [28,34]. The MMSE-LE also turns out to be the cascade of a matched filter and a transversal filter operating at symbol rate [34]. Due to the noise enhancement caused by the equalizer, the decision error probability is larger than the matched filter bound [35]. As a result, satisfactory performance cannot be achieved with channels having severe amplitude distortion when using LE.

Subsequently, Austin [36] proposed the non-linear Decision Feedback Equalizer (DFE) to mitigate the noise enhancement. The DFE consists of a forward LE, which combats noise and pre-cursor ISI. The post cursor ISI equalization is performed with decision feedback as shown in figure 2.2.

![Figure 2.2: Decision Feedback Equalizer](image)

The DFE's forward LE can take the form of a ZFE which attempts to remove all ISI or the MMSE-LE, which minimizes the MSE between the data signal and the output of the equalizer. Due to the noise enhancement in LE, the MMSE criterion is preferred and leads to the MMSE-DFE [37]. Noise enhancement is greatly reduced because, not only is the pre-cursor eliminated by the feed forward filter, but the post-cursor ISI is removed by feeding back the receiver's decisions through the feedback filter and subtracting the post-cursors of the previous symbol. It is shown in [38] that the front end of the MMSE-DFE is the mean-square whitened matched filter (MS-WMF). It is, in effect, a cascade of a noise-whitening filter and a matched filter. The form of the filter depends on the Signal-to-Noise-Ratio (SNR). At high SNR it approaches the whitened matched filter (WMF) [34], which is the optimum front end for the ZF-DFE (and MLSE). As the SNR approaches zero, the MS-WMF approaches the matched filter (MF) [38], which does not remove the ISI. The MMSE-DFE is designed to minimize the

...
noise under the assumption that the correct decision is fed back [38] and therefore results in error propagation when incorrect decisions dominates in the low to mid SNR region. Belfiore and Park [35] introduced a new DFE structure called the predictive DFE, which made use of a linear predictor as the feedback filter and showed its equivalence to the conventional DFE for infinite-length filters. This structure is useful when a DFE is combined with a sequence estimator for equalization and decoding of trellis-coded modulation on ISI channel [39].

Sequence Estimation

The optimum receiver (in the sense of minimizing sequence error probability) in the presence of ISI is the Viterbi Equalizer (VE). It exploits the correlation between successive received filtered samples for making a decision about the entire sequence using a dynamic programming algorithm, operating on matched filter output samples taken at symbol rate. The idea of using the VA to mitigate ISI was first demonstrated by Forney [40]. His receiver consisted of a WMF i.e., a MF followed by a transversal filter (that whitens the noise), a symbol rate sampler, and a recursive non-linear processor that employs the VA so as to perform MLSE. Subsequently, Ungerboeck derived a similar scheme but without the WF. His receiver employed a modified VA that operated directly on the MF output without whitening the noise [41]. The modified VA incorporates the WF into its metric computation. Both receivers have very similar structures as shown in Figure 2.3. Acampora [42] used the MLSE for combining convolutional decoding and equalization, and extended the application of MLSE to QAM systems [43]. These receivers need the trellis based VA to solve the MLSE problem recursively when the channel memory is finite.

Reduced-Complexity MLSE Equalizers

MLSE has a complexity that grows exponentially with the size of signal constellation and the length of channel impulse response. It is desirable to reduce the complexity while retaining most of the performance. Various approaches are described in [44–46]. In the beginning, considerable efforts were made to shorten the channel impulse response. In a scheme analysed by McLane [47], residual interference terms were not taken into account by the detector and caused severe propagation errors. Another
2.2. Equalization Techniques

approach is to use LE or DFE to estimate the input sequence and use these estimates to cancel the tail of the ISI in the received sequence prior to passing it to the VA [46]. However, pre-filtering still results in significant error propagation and high error rates [46].

Another approach for reducing the complexity of MLSE lies in simplifying the Viterbi algorithm itself. By employing suitable decisions, Vermuelen [48] and Foschini [49] observed that only a small number of likely paths need to be extended to obtain MLSE performance. Wesolowski [50] employed the DFE to determine a small set of likely signal points and then used the VA to find the most likely sequence path through a reduced-state trellis.

Recently two novel reduced state sequence estimation techniques have been proposed. Duel-Hallen and Heegard devised the DDFSE algorithm [44] to reduce the number of states. The complexity of the algorithm is controlled by a parameter $\mu$ and can vary from 0 to the memory length of the channel. When $\mu = 0$, DDFSE reduces to DFE and when $\mu$ equals to the channel memory length, $L$, it become MLSE. For the intermediate values of $\mu$, $0 < \mu < L$, the algorithm functions as a reduced state VA with feedback incorporated into the structure of the path metric computations [44]. Each state of the DDFSE trellis provides only partial information about the full state.
2.2. Equalization Techniques

of the channel, and the algorithm uses the best path (survivor) leading to each state to compute the metric. An estimate of the partial state is stored in the decision feedback filter extracted from the best path. Hence, the remaining ISI taps are the post-cursors that are cancelled using decision feedback on a per survivor basis as shown in figure 2.4. Chevillat and Eleftheriou [51] independently proposed the same algorithm but for a finite length channel, while the DDFSE developed by Duel-Hallen et al [44] is a generalized algorithm, which includes channels with finite and infinite impulse responses.

![Figure 2.4: DDFSE and RSSE structure](image)

Equalization for large signal constellations have been addressed by Quershi and Eyuboglu in [45]. In addition to introducing feedback into the structure of the path metric computations, they proposed to reduce complexity further by using the ideas of set partitioning. The signal set is divided in a manner to Ungerboeck Trellis Coded Modulation (TCM) partition [52]. This results in an algorithm known as the RSSE. It was found that the required complexity to achieve the performance of MLSE is independent of the size of the signal set for large enough signal sets [45]. It is also shown in [45] that the DDFSE is a special case of RSSE. Later in [53], Qureshi et al show how RSSE can be applied to the combined trellis of the code and ISI, and in [51] how reduced state decoding can lead to much better results, when working on a combined ISI-TCM trellis, compared with a LE followed by TCM decoding. As in DDFSE, the RSSE's performance is limited by error propagation caused by the premature decisions when selecting the best path leading to each subset state to compute the branch metric. Under extreme cases of set partitioning, the RSSE reduces to DFE [45].
2.3. Pre-filter

One particular problem with the RSSE and DDFSE approaches is that they need to be tailored to a particular type of OCIR so that the best choices of subsets or the best choices for DFE can be made. There exists another class of reduced complexity algorithms known as the Reduced-search algorithms. These algorithms make the choice of state reduction based on the data itself at each epoch. The M-algorithm (M-A), proposed by Anderson et al [54], is a 'breadth-first' search as it searches across states at a given symbol epoch. It makes hard decisions similar to the VA [54,55] and retains only the best M paths at each depth (time). In effect, it searches only a small sub-trellis. When M=1, it reduces to DFE. Therefore the required complexity depends on the number of paths retained. As in RSSE, the M-A works best on minimum phase channels [55].

The T-algorithm (T-A) proposed by Simmons [56], is similar to the M-A except that instead of keeping a fixed number of paths, it keeps those paths with an accumulated metric less than some threshold. Hence, the number of paths kept will vary for each symbol period. In [57], Simmons and Sensyshyn evaluate the performance of M-A, T-A and RSSE over the reduced trellis of the combined code and channel, for several channels. They found that for a given number of paths retained, the T-A resulted in the lowest BER, while the M-A is much better than the RSSE and all these methods approach the performance of VA as the number of states increases. However, the main problem of reduced search algorithms is that the processing delay is not constant or unknown. These disadvantages are pointed out in [57], that the M-A and T-A cannot match the high degree of parallelism and regularity that is offered by VA and RSSE. In addition, substantial state or metric search is required to justify the use of M-A and T-A. Hence the RSSE and DDFSE are still preferred choice for complexity reduction in EDGE [8].

2.3 Pre-filter

Spectral factorization of the channel auto-correlation has been demonstrated by Forney [40], which results in the WMF approach and subsequently the use of VA to mitigate ISI. The aim is to first remove the noise correlation that is introduced by matched filtering
2.3. Pre-filter

(matched to received pulse) so that the noise remains 'white' prior to the VA detector. The significance is, the channel seen by the VA has a specific characteristic, which can be a minimum or maximum phase equivalent. Minimum phase channel implies that its transfer function has zeros and poles that both lie within the $z$-transform unit circle. Therefore, the impulse responses are concentrated near the zero delay tap and vice versa for maximum phase equivalent channel. Minimum phase channel impulse responses are critical to ensure good performance of the reduced state (RSSE and DDFSE) and reduced search algorithms (M-A) [44,45,51,55].

The WF has an infinite length anti-causal response [40]. It is shown that the anti-causal (infinite length) DFE feed forward filter, optimized according to the zero-forcing criterion, results identically to the ideal canonical WF, while the causal DFE Feedback filter is identical to the strictly casual part of the equivalent channel in [55]. However, with the finite-length constraints, a popular method is to apply the feed forward filter of the MMSE-DFE for pre-filtering. Reasonable FIR approximation of the desired allpass transfer function can be expected [39]. However, the direct calculation of MMSE-DFE turns out to be complex as it requires matrix inversion. In [58] Al-Dhair and Cioffi proposed the fast Cholesky factorization to compute the DFE. Several improved versions of this algorithm have been derived in [59,60] which are more modular and avoid the square root operations. It was shown in [60] that the MMSE-DFE method is not robust to a mismatch of design parameters and the solution is sensitive to the selection of the noise variance which has to be considered as a free parameter for the filter design. The robustness can be increased by fractionally-spaced pre-filtering as shown in [60], which also increases complexity. Subsequently, Gerstacker [8] proposed a completely new and robust technique that involves LP. The method has a moderate complexity and it only requires the order of the prediction error filter as the parameter input. It is pointed out in [19] that the pre-filter using LP of up to order 25 can be calculated via the LD algorithm in a practical receiver without violating the limitations imposed by the real-time environment.
2.4 Joint Estimation of Channel and Data

Adaptive MLSE

Various kinds of adaptive MLSE have been developed as in [31, 41, 46]. The adaptive MLSE generally consist of a channel estimator and an MLSE (also known as the conventional adaptive MLSE) and is shown in Figure 2.5. In the adaptive MLSE, a transmitted information sequence is estimated by the MLSE based on the channel impulse response that is estimated by the channel estimator using the decision sequence derived in the MLSE. As the decision delay is inherent in the VA, the MLSE cannot avoid a channel estimation delay in tracking the time-varying channels. In order to reduce this delay two approaches have been adopted. The first is that the channel impulse response is estimated by using the tentative decisions from the MLSE, which are obtained by truncating the surviving length path history on the VA to some fixed length as such those in [31, 41, 46]. The second approach estimates the channel impulse response by an adaptive DFE embedded in the MLSE as in [46]. Although the second approach can estimate the CIR without delay, it is impaired by the error propagation caused by the DFE [46]. Shortly after Forney demonstrated the mitigation of ISI using the VA, Magee and Proakis proposed an adaptive MLSE structure, which is composed of the Forney’s scheme but with an additional channel estimator to cope with the slowly time-varying time dispersive channels [31]. Subsequently, Ungerboeck further developed a new approach avoiding the WF and extending it to a fully adaptive structure [41], which has robustness to a sampling timing error.

Figure 2.5: Conventional Adaptive MLSE Receiver
2.4. Joint Estimation of Channel and Data

Per-Survivor Processing

An alternative to the above classical approach is presented by Kubo [61] as shown in figure 2.6, where data-aided estimation techniques are used, which are not influenced by the fixed decision delay embedded within the VA.

At about the same time, Raheli et al [62] introduced the concept of Per-Survivor Processing (PSP), which has a similar structure in [61]. PSP is being established for sequence detection in uncertain environments, which utilizes a set of estimators of the unknown parameters, where each estimator is data-aided by each hypothetical data sequence [62] as shown in figure 2.6. Typically, sequence detection is performed by VA that searches a trellis diagram for the maximum likelihood path. Due to the uncertainty, especially in a time varying channel, the computation of the transition metrics requires additional information, which in PSP is obtained by data aided parameter estimation based on the survivor sequences. In fact, PSP was first applied to the cancellation of residual ISI in RSSE [63]. In [64] applications including joint decoding and phase synchronization of trellis-coded modulated signals are also addressed.

The concept of Minimum Survivor Processing (MSP) [27], that has a lower complexity compared with PSP has been proposed by Castellini et al. Good performance of this scheme has also been demonstrated in typical GSM environments in [26, 27]. The difference between MSP and PSP lies in the number of channel estimates to be stored and updated. In MSP, a single channel estimate is carried along and updated during the
2.5. Soft-Decisions

The symbol-by-symbol Maximum A Posteriori (MAP) algorithm was formally presented in 1974 by Bahl et al. as an alternative to the VA for decoding convolutional codes [67]. While the VA minimizes the probability of sequence error, the MAP minimizes the probability of symbol error. The MAP algorithm presented in [67] is known as the BCJR algorithm. It is based on Chang and Handcock’s method for the removal of ISI that was presented in 1966 [68]. A different version of the MAP algorithm was presented by Abend and Fritchman for the same application [69]. Following the convention in [13] the algorithms in [67] and [68] are known as type I MAP algorithm which requires a forward and backward recursion and is therefore suitable for block oriented processing. The algorithm of [69] is known as the type II MAP algorithm that only requires forward recursion and is suitable for continuous processing.

The goal of the MAP algorithm is to find first the A Posteriori Probability (APP) of each state transition, message bit or code symbol produced by the underlying Markov process, given the noisy received sequence. The BCJR algorithm is optimal for estimating the states and outputs of a Markov process in the presence of White Noise [67].

recursive trellis search. In [63], Raheli et al investigated the performance of arbitrary numbers of parameters, which resulted in an algorithm that compromises between tentative decisions and PSP. The algorithm utilizes an arbitrary number of parameter estimators ranging between one (tentative decisions) and the number of retained paths (PSP).

In extreme channel dynamics, one sample per symbol may not provide adequate performance. In [65] Vitetta et al found that improvement in the receiver error performance in fast fading is obtained if the detector processes more than one sample per symbol, and results in a substantial lowering of error floor. In [66], the concept of Per-Branch Processing (PBP) is introduced as a general case of PSP, which has the advantages of PSP and most important of all, in PBP, it operates on multiple samples per symbol where the channel estimate is updated many times during the hypothesized symbol transitions.
2.5. Soft-Decisions

However, it is rather complex to implement because the computations are carried out in the probability instead of the logarithmic domain, this results in a large number of multiplications and logarithmic operations. Also the numerical representation of very low probability values is difficult in the probability domain [70]. In order to reduce these problems, realizations of this algorithm in the logarithmic domain have been proposed by Robertson et al [14], which resulted in useful simplifications known as the Log-MAP and Max-Log-MAP. In [71], the Log-MAP, which requires estimation of the noise variance, is found to be more sensitive to mismatched channel estimation than the sub-optimal algorithms.

The BCJR algorithm has a complexity that is exponential with the length of the channel impulse response in the case of ISI. If the overall channel memory is large, the complexity of a BCJR algorithm, even with the cited logarithmic simplifications [14], may still be unacceptable because of the trellis size and hence in [72], the reduced state MAP algorithms are used for equalization. Recently, in [70] the reduced state BCJR type algorithms were being generalized. Several applications including coherent detection for ISI channels, non-coherent detection and detection based on LP for Rayleigh flat-fading channels are also being addressed. Other reduced complexity methods that involves the M-A and T-A are investigated in [73].

Another approach to obtain soft-decisions is to modify the VA. Hagenauer and Hoeher developed the Soft-output Viterbi Algorithm (SOVA) algorithm for a binary system [74] which generates a reliability value for each bit of the hard decision. In their approach to mitigate the effects of frequency selective fading channels, the concatenation of the SOVA and the VA decoder is employed. It is shown in [75] in the binary case that the degradation on performance compared with the MAP algorithm is small.

A third type of MAP known as the Optimum Soft Output Algorithm (OSA) was developed by [13]. The OSA is an improved version of the type-II MAP algorithm as it generates optimum soft outputs that require only a forward recursion. Although, it significantly reduces the memory and computation requirements of type-II MAP algorithms without any performance degradation, it still requires knowledge of noise variance and probability domain operations as in the MAP algorithms. In order to
overcome these disadvantages, Li et al developed the SSA [13] at the expense of sacrificing some optimality. In addition to the operations needed by the VA, the SSA needs to store a soft survivor matrix for each state and update it recursively. Like the VA, the Add-Compare-Select (ACS) remains the main operation of the SSA.

2.6 New Research work

Due to their tradeoffs between performance and complexity and their high regularity, the reduced state algorithms are preferred over the reduced search algorithms. In this work the combination of DDFSE and RSSE is proposed to curb the long channel memory and 8-PSK modulation format of EDGE. The initial approach to reducing the complexity of the VE is to approximate the full trellis by a smaller set using decision feedback to cancel the residual ISI on per-survivor basis. This results in the use of DDFSE and is shown to be capable of equalization in EDGE in [9,16]. The possibility of further reducing the complexity using RSSE was first proposed and investigated in this work [17,18] and at about the same time [19] confirms this possibility with theoretical analysis. The work reported in [17,18] is sensitive to the channel phase as it involves reduced state algorithms. This has been overcome with a pre-filter. For complexity reduction, the LP technique is preferred over the DFE method. However, the work reported here makes use of the Schur algorithm instead of the LD proposed in [8], so as to exploit the advantages of parallelism as in [15]. Combining the proposed pre-filter and the reduced state algorithm (DDFSE and RSSE), a low complexity equalization structure is established.

In EDGE, five MCS modes have been defined for EGPRS and therefore the concatenation of the equalizer and the channel decoder provides a powerful means of improving the receiver performance. A joint coding and equalization scheme involving the logarithmic BCJR MAP and a VA decoder is proposed. Two logarithmic MAP derivatives, the Log-MAP and Max-Log-MAP [14] are considered for reducing the computation requirements of MAP. For trellis reduction, the decision feedback mechanism of DDFSE is applied and results in the 8 state SO-DDFSE.

The main disadvantage of the SO-DDFSE is that it requires an additional backward
recursions to deliver the soft outputs. The SSA, a sub-optimal method developed by Li et al [13] does not require knowledge of noise variance and requires forward recursion to deliver the soft decisions. However, like the VA, the full state SSA is too complex for implementation in EDGE. In this work, the concept of DDFSE is applied to the SSA. As a result, a much simpler method called RS-SSA has been developed, which has a much lower complexity than the SO-DDFSE but with some performance trade off even though both have the same number of trellis states. Nevertheless, it serves as another possible option to SO-DDFSE for complexity reduction.

In order to further reduce the complexity of SO-DDFSE, the RSSE algorithm is introduced to the BCJR MAP where finer tradeoff options between complexity and performance can be achieved. This results in two more reduced state options, the 4 and 2 state SO-RSSE. The effect of reduced states on the performances are evaluated and addressed. In addition, the effect of Max-Log-MAP simplification on SO-RSSE is also investigated.

A new and improved two stage soft output RSSE (CSO-RSSE), which involves the RSSE and a Log-MAP algorithm in cascade is proposed. The intention is to separate the Log-MAP from the sequence estimator so that the final hard decisions from the first stage are used as decision feedback for truncating the trellis of Log-MAP in the succeeding stage so as to mitigate the disadvantages of single stage, reduced state Log-MAP. The advantages offered by the two stage scheme is:

**Reduced decision errors**

The decision errors are inherent in reduced state algorithms where tentative decisions for each survivor are fed back to cancel the post-cursor ISI. In the two stage method, the final hard decisions are decided based on the best path metric accumulated at the end of the sequence estimation in the first stage, which is more reliable than for a single stage.

**Better noise variance estimation**

In interference limited environments, the perturbation consists a mixture of thermal noise and interference where the overall statistical nature is unknown [76].
2.7. Conclusions

In the cascaded scheme, the noise variance is estimated based on the hard decisions, which use a longer average over the data symbols and hence results in a less biased estimate.

Finally, a joint channel and data estimation scheme is adopted as the strategy to combat the fast time-varying ISI. Although there is similar work being done for equalization in GSM [24–27], all involves the MLSE algorithm. In the current work, an adaptive RSSE/DDFSE is proposed to avoid the complexity requirements of a MLSE. The PSP approach is adopted. This is because RSSE and DDFSE is inherently a PSP structure, as the residual ISI is cancelled on per survivor basis [45,51,63]. Additionally, the pre-filter coefficients are jointly updated using the LMS algorithm so as to maintain low computation effort. Finally, the joint scheme is extended to the proposed soft-output algorithms to cope with rapid channel dynamics such as the case of a high speed train.

2.7 Conclusions

This chapter has performed a review on the various equalization techniques. Based on the literature review, a brief description of the research undertaken is presented in this thesis whereby the DDFSE and RSSE are identified as the possible candidates for reduced complexity equalization in EDGE. Applying the DDFSE or RSSE to the MAP derivatives (Log-MAP and Max-LOG) and SSA, soft-output algorithms of modest complexity are obtained and are shown as being able to improve the detection reliability especially over interference limited channels. The PSP with LMS tracking is also adopted as the strategy for mitigating ISI on channels with fast dynamics. Finally, the PSP scheme is extended to incorporate soft-outputs.
Chapter 3

System and Channel Model

3.1 Introduction

This chapter gives an overview to the EDGE communication system model used for the evaluating the performance of the receiver. As shown in figure 3.1, it covers the modelling of EDGE transmitter, receiver, multi-path fading channels and also the channel impairments that include thermal noise and CCI. The channel estimation and synchronization procedure that involves the LS approach is also presented.

3.2 EDGE Communication System

Figure 3.1 shows the overview simulation model of the EDGE communication. Five basic elements, the channel coder, burst formatter, modulation and pulse shaping constitute the EDGE transmitter. The propagation is characterized by a time-varying frequency selective fading channel that is implemented by a linear time-varying transversal filter. The transmission is perturbed by both thermal noise and CCI, which are modelled as AWGN and additive noise respectively. At the receiver, the front end filter is represented as a low pass filter. The channel estimation block synchronizes to the received signal and derives a set of parameters required by the trellis equalizer. Finally, the detected bits are then de-interleaved, de-punctured and decoded using the VA.
3.2. EDGE Communication System

Figure 3.1: EDGE communication System - Complex Baseband Model
3.2. EDGE Communication System

3.2.1 Channel Coding

At the transmitter, the incoming data bits sequence, \( \{a_i\}_{i=1}^{L_0}, \ a_i \in \{0,1\} \) of length \( L_0 \) is delivered in 20msec blocks. They are initially encoded using rate \( R_c = 1/3 \) convolutional code with constraint length 7 [2]. The coded stream is punctured and interleaved for protection against fading according to the required MCS mode. The interleaved bits and header field bits (header, uplink status flags and stealing bits) are distributed over four bursts as shown in figure 1.3.

3.2.2 Modulation and Pulse Shaping

The modulation process in EDGE takes an extra step in continuously rotating the 8-PSK constellation by \( \frac{3\pi}{8} \) radians so that the envelope avoids the origin. This is not implemented in the simulation for simplicity. Moreover, the transmitted constellation can be seen as having two 8-PSK constellation planes offset by \( \frac{3\pi}{8} \) radians and swapping from one plane to another at every consecutive symbol time, resulting in a 16-PSK constellation. The decision making process in the receiver approximates that of 8-PSK since there is a change in plane from one symbol to next.

Nevertheless, the transmitted 8-PSK symbol can be expressed as \( x_k \in \{e^{j2\pi m/8}\}, \ m \in \{0,1,\ldots,7\} \) where \( x_k = F(b_{k;0}, b_{k;1}, b_{k;2}), \ b_{k;i} \in 0,1 \) is the encoded stream at the output of the burst formatter. The function \( F(\cdot) \) performs the Gray mapping and 8-PSK modulation as shown in figure 3.2 [77]. The output of the 8-PSK modulator is shaped by the transmit filter which is a LGMSK pulse with BT=0.3, spanning the time interval \( 0 \leq t \leq 5T \) as shown in figure 3.4. The transmitted waveform is

\[
s(t) = \sum_k x_k C_0(t - kT) \tag{3.1}
\]

where \( C_0(t) \) is the impulse response of the LGMSK transmit filter and \( T \) is the symbol period. The LGMSK pulse in figure 3.4 is obtained using the Laurent decomposition technique [78]. The LGMSK pulse containing over 99% of the energy is decomposed into factors of Laurent component sine using (A.1) as shown in figure 3.3 and 3.4. After modulation and pulse shaping the signal is then transmitted over four time slots [79] as shown in figure 3.5.
3.2. EDGE Communication System

\[ F(b_{k:0}, b_{k:1}, b_{k:2}) = \]

Figure 3.2: EDGE 8PSK Constellation

Figure 3.3: Laurent Decomposition
3.2. **EDGE Communication System**

![Figure 3.4: Frequency and Impulse Response of LGMSK-0.3](image)

**Figure 3.4:** Frequency and Impulse Response of LGMSK-0.3

![Figure 3.5: EDGE Burst and Framing Format](image)

**Figure 3.5:** EDGE Burst and Framing Format
3.3 Wideband Propagation Channel

The transmitted signal is subjected to the following impairments: Multi-path fading and Doppler spreading. In the EDGE system, the mobile radio environment between the base station and the MS is characterized by a highly dispersive multi-path resulting in frequency selective fading. The EDGE standard adopted the tapped delay line model that uses discrete multi-path rays to represent real life propagation parameters for Rural Area (RA), Hilly Terrain (HT), Typical Urban area (TU) and a model for Equalization test (EQ) [80] as tabulated in appendix C. The parameters are the time delay, average power and type of fading (Rayleigh or Rice) of the taps in 12 and 6 tap settings. This is used together with the speed of the MS for simulating the radio channel. The notation used refers to a propagation condition in the two letter name and speed in km/h; TU50, for instance, denotes an MS travelling at 50 km/h in urban area.

3.3.1 Multi-path Fading

The channel is modelled by $l$ discrete multi-path components as shown:

$$c'(t) = \sum_{\nu=0}^{l-1} \rho_{\nu}(t) \delta(t - \tau_{\nu}(t)) \tag{3.2}$$

The $l$ tap settings of complex gains $\{\rho_{\nu}(t)\}_{\nu=0}^{l-1}$ and delays $\{\tau_{\nu}(t)\}_{\nu=0}^{l-1}$ are associated with the discrete multi-path components as defined in [80] and $\delta(\cdot)$ is the Dirac Delta function. Although the 12 tap setting is much preferred, the 6 ray model is used to reduce the simulation time. Among the four channels, EQ consists of 6 rays equally spaced apart and has the worst ISI followed by the TU which is a more realistic scenario. The appropriate speed corresponding to each channel is also specified as shown in Appendix A.

3.3.2 Doppler Spreading

Since the MS will be moving, the angle of arrival must be taken into account as it affects the Doppler shift associated with a wave arriving from a particular direction.
Echoes of identical delays arise from reflectors located on an ellipse. A typical and often assumed shape for the Doppler spectrum for mobile fading channel is the classical Doppler spectrum and is given by the Classical power spectral density [81]:

\[
S(f) = \begin{cases} 
\frac{2\sigma_d^2}{\pi f_D \sqrt{1-f/f_D}}, & |f| \leq f_D \\
0, & |f| > f_D 
\end{cases} 
\] (3.3)

where \( f_D \) is the maximum Doppler shift and the variance \( \text{Var}\{\rho_v(t)\} = 2\text{Var}\{\text{Re}\{\rho_v(t)\}\} = 2\sigma_d^2 \). The other common Doppler spectrum is known as the Ricean, where the sum of a classical Doppler spectrum and one direct path or Line-of-Sight path is constituted as in:

\[
S(f) = \begin{cases} 
\frac{A_1\sigma_d^2}{\pi f_D \sqrt{1-f/f_D}} + A_2\delta(f - A_3f_d), & |f| \leq f_D \\
0, & |f| > f_D 
\end{cases} 
\] (3.4)

where \( A_1, A_2 \) and \( A_3 \) are constants that are specified in the EDGE standards [80]. The amplitude of each ray is Rayleigh distributed and varies according to the Doppler spectrum depending on the simulated propagation channel except for the first ray in the RA channel which is a Rice process. The method of Exact Doppler Spread (EDS) [81] is adopted here for generating fading coefficients. Figure 3.6 shows a snapshot of the first ray of the RA channel using the EDS technique. In order to verify the fading simulator the theoretical and simulated pdf curves are compared in figure 3.7. The corresponding level crossing rate \( N_r \) and average fade duration, \( T_d \) are obtained as shown in figure 3.8 and 3.9. In this example the Rayleigh process is assumed instead.

### 3.3.3 Channel Simulator

The received signal without interference is

\[
z(t) = \sum_{\nu=0}^{l-1} \rho_v(t)s(t - \tau_v(t)) 
\] (3.5)

The channel impulse response (CIR) that includes the transmit filter and the time-varying channel is given by \( c(t) = c'(t) \otimes C_0(t) \) and \( \otimes \) denotes convolution. The received pulse is obtained by summing the delayed and sampled version of the shaped pulses corresponding to each ray. The shaped pulses are multiplied by the fading
coefficients corresponding to that time period in the time slot. These pulses form the 
discrete time time-varying CIR, \( \{ c_i(t) \}_{i=0}^{N-1} \). It is modelled by a \( N \) tap time-varying transversal filter that has tap spacing equal to \( \frac{T}{N_s} \) and therefore for single user, the transmitted signal is represented by

\[
 z_k = \sum_{i=0}^{N-1} c_{ki} x_{k-i} \tag{3.6}
\]

where \( N_s \) is the number of samples per symbol, which corresponds the resolution of the simulation system.

### 3.3.4 Frequency Hopping

Slow Frequency Hopping (FH) is part of the standard in EDGE. When no FH is used, it is assumed that the radio bursts are transmitted on a single carrier with continuous second order fast fading characteristics. This means that if a burst is currently experiencing a fade in the received power, then it is likely that subsequent bursts may experience similar fading. However, with slow FH, the MS will transmit or receive on a
3.3. Wideband Propagation Channel

Figure 3.7: Probability Density Function, $p(|\rho_0(t)|)$

Figure 3.8: Average Fade Duration (AFD) of $\rho_0(t)$, $f_D = 208\text{Hz}$, RA250
fixed frequency for one time slot and then hop before the time slot of the next TDMA frame [80]. This provides interference diversity at the receiver as all bursts in a frame with similar fading is greatly reduced. However as specified in the standard, the ideal FH is assumed when evaluating the performance of the receiver. The ideal FH is implemented in the simulator by applying to each burst an independent Rayleigh process. As the interleaving depth of the packet switched network is limited to four bursts then the fading characteristics of all bursts within a single radio block are uncorrelated, thereby emulating ideal FH.

3.4 Interference

In EDGE, users are orthogonal within a cell because of the time separation, therefore the CCI purely originates from the surrounding cells. The interfering signals and the wanted signal are subjected to the same but independent propagation profiles as seen in figure 3.10. In a real network, more interferers further from the cell centre exist but
they contribute less to the total interference as the distance is increasing. Hence, the CCI can be modelled as additive noise to the wanted signal. In the case of FH, the interference and the wanted signal all assume the same frequency hopping sequence [80]. For $N_f$ co-channel users, the interference can thus be modelled as:

$$I(t) = \sum_{i=1}^{N_f} \sum_{n=0}^{N-1} c_n^{(i)}(t)x_{t-nT}^{(i)}$$  \hspace{1cm} (3.7)

In the presence of ISI, CCI and thermal noise the transmitted signal is

$$z(t) = \sum_{n=0}^{N-1} c_n(t)x_{t-nT} + \sum_{i=1}^{N_f} \sum_{n=0}^{N-1} c_n^{(i)}(t)x_{t-nT}^{(i)} + \eta(t)$$  \hspace{1cm} (3.8)

The thermal noise $\eta(t)$ is assumed to be the complex zero mean AWGN with variance $\sigma^2 = \frac{1}{2} E[|\eta(kT)|^2] = N_0$. $N_0$ refers to the single sided power spectral density (Watts/Hz) and $E[.]$ denotes statistical expectation.

### 3.5 Receive Filter

In figure 3.1, baseband signals are first filtered by a low pass filter and then sampled at rate $\frac{1}{T}$ prior to the sequence estimator, as opposed to the optimum scheme in [40] where a noise WMF matched to the CIR is used. This is because the channel is time varying and unknown a priori. This requires an adaptive WMF that is computationally
3.6 Synchronization and Channel Estimation

complex. Instead a fixed low pass filter is used to avoid noise whitening for simplicity. In fact such a filter exist in the band-pass filter of the receiver [82], which also satisfies the adjacent channel requirements. Thus no additional anti-aliasing filter is required before base-band processing. However for the investigation, the low pass equivalent of the band-pass filter mentioned in [82] is assumed. It consists of two Butterworth filters in cascade, both ideally equalized, the first with 7 poles, the second with 5 poles and having a 3dB bandwidths of $\frac{1.625}{T}$ and $\frac{0.5}{T}$ respectively.

The $k^{th}$ received symbol is sampled at rate $1/T$ and the output of the filter:

$$r_k = \sum_{i=0}^{L} h_{i,k} x_{k-i} + \eta_k$$

(3.9)

where $\eta_k$ is the noise samples at the output of the receive filter and $\{h_i(k)\}_{i=0}^{L}$ is the discrete time Overall CIR (OCIR), that consists of the CIR and the receive filter.

3.6 Synchronization and Channel Estimation

Trellis based equalizers require knowledge of the multi-path fading channel. The parameters characterizing the channel which must be estimated are:

- Complex OCIR coefficients, $\{h_i\}_{i=0}^{L}$
- Noise variance, $\sigma_n^2$

The received signal of length $N_B$ is low pass filtered and over-sampled by a factor of $R$. The over-sampled sequence $\tilde{r}_n$ is stored in a buffer, which is necessary as the TS that provides an initial state to the equalizer is located at the center of the time slot. The channel parameters are estimated based on the LS method [83] whereby the OCIR estimate $\{h_i\}$ is obtained by computing the cross-correlation of the known TS, $\{d_i\}_{i=1}^{N_{TS}}$ and received TS

$$R_{dd}(n) \approx \frac{1}{N_{TS}} \sum_{i=0}^{N_{TS}-1} d_i^* \tilde{d}_{n+i} \approx h_n$$

(3.10)
3.6. Synchronization and Channel Estimation

The sequence \( \{\tilde{d}_n = \tilde{r}_{n+(\tau_d-1)R}\} \) is such that it contains the TS, which is ensured by extracting the extra samples preceding and succeeding the \( N_{TS} \) most central symbol time duration of \( \tilde{r}_n \) and \( \tau_d \) is the extraction position of TS.

The optimum sampling instant \( \tau' \) is first determined such that the power of the \( T \)-spaced \( (L + 1) \) samples contained in \( \{\tilde{h}_i\} \) is maximized:

\[
\tau' = \max_j (E_j) \tag{3.11}
\]

where

\[
E_j = \sum_{i=0}^{L} |\tilde{h}_{R_i+j}|^2 \tag{3.12}
\]

Using the best sampling index \( \tau' \), the \( T \)-spaced OCIR estimates \( \{h_i\}_{i=0}^{L} \) are obtained as follows

\[
h_i = \tilde{h}_{J+R_i} \quad i = 0, \ldots, L \tag{3.13}
\]

Figure 3.11 a shows an example snap-shot of the TU50 channel estimated using LS approach. Timing synchronization is achieved using (3.11) such that the estimated channel’s energy is maximized within a window of \( (L + 1) \) \( T \)-spaced samples. The channel estimates is down-sampled to rate \( \frac{1}{N} \) as shown in Figure 3.11b using (3.13). The TS is located at \( \tau_{TS} \). Due to propagation, the TS is found located at \( \tau' + (R\tau_d - 1) \) in the received burst. This implies that the received burst is offset by \( \tau = \tau' + (R\tau_d - 1) \). With the established synchronization, the corresponding received signal is down sampled to rate \( \frac{1}{N} \) such that

\[
\tau_k = \tilde{r}_{\tau+R_k}, i = 0, \ldots, N_B - 1 \tag{3.14}
\]

The noise variance required by the soft output algorithm is estimated after pre-filtering since it is inserted prior to the trellis equalizer. This requires a set of parameters, the pre-filter coefficients and the estimated transformed OCIR (TOCIR) for bi-directional equalization to be computed based on the estimated OCIR. The pre-filtered received signal for forward and backward equalization can then be expressed as in (3.15) and
3.6. Synchronization and Channel Estimation

Figure 3.11: Estimated TU50 channel

\[(3.16)\] respectively as shown

\[y_k = \sum_{i=0}^{L} f_i x_{k-i} + n_k \]  
\[v_k = \sum_{i=0}^{L} b_i x_{k-i} + n_k \]  

where \(\{f_i\}_{i=0}^{L}\) and \(\{b_i\}_{i=0}^{L}\) are the estimated TOCIR and \(n_k\) is the 'white' noise [19] samples after pre-filtering. The noise variance \(\sigma_n^2\) is obtained by computing the distance between the pre-filtered TS and the known TS \(\{d_k\}_{k=1}^{N_{TS}}\) as shown:

\[\sigma_n^2 = \frac{1}{N_{TS}} \sum_{k=1}^{N_{TS}} \left| \tilde{v}_{k+r_{TS}} - \sum_{i=0}^{L} \tilde{h}_i d_{k-i} \right|^2 \]  

where \(\{\tilde{v}_k\}_{k=1}^{N_{BS}}\) represents either the forward or backward pre-filtered received sequence and likewise \(\{\tilde{h}_i\}_{i=0}^{L}\) for the estimated TOCIR. The above channel estimation method is performed on a per time slot basis and therefore the channel is assumed to be quasi-stationary. For dynamic channels the properties can vary significantly within the time
3.7 Simulation Environment

The simulation is based on the EDGE system described in the section 3.2. The simulation system has a resolution of $N_s$ samples per symbol. Assuming the AWGN is bandlimited by a baseband anti-aliasing ideal low pass filter with cutoff frequency equal to half the sampling rate ($f_s$), the noise variance with a noise bandwidth $B_n$ is

$$\sigma_n^2 \triangleq N_0 B_n = N_0 f_s$$  \hfill (3.18)

The Signal-to-Noise (SNR) ratio is defined as

$$SNR \triangleq \frac{P_s}{P_n} = \frac{E_s}{N_0} \left( \frac{R_s}{f_s} \right)$$  \hfill (3.19)

$$= \frac{E_b}{N_0} \left( \frac{R_c N_b}{N_s} \right)$$  \hfill (3.20)

where the average noise power, $P_n = \sigma_n^2$, $R_s$ is the symbol rate, $R_c$ is the code rate of the MCS mode and $N_b$ is the number of bits per symbol. The average symbol energy is $E_s = N_b R_c E_b$ and $E_b$ is the average symbol energy per bit. The average signal power over the $N$-tap time-varying CIR $\{c_i \}^{N-1}$ is

$$P_s = \sigma_x^2 \sum_{i=0}^{N-1} E \left[ |c_i|^2 \right]$$  \hfill (3.21)

where $\sigma_x^2 = E \left[ |x_k|^2 \right] = N_s$

A single co-channel interferer that has fading independent of the desired signal’s channel is considered. The interference is measured by the Signal-to-Interference-plus-Noise ratio (SINR). It is defined as the ratio of the wanted signal power to the CCI and thermal noise.

$$SINR \triangleq \frac{P_s}{P_{R} + P_n} = \frac{P_s}{\sigma_f^2 + \sigma_n^2}$$  \hfill (3.22)
where the $P_I = \sigma_I^2$ is the average CCI power. Based on the definition in (3.19), the Signal-to-Interference (SIR) ratio is defined as

$$SIR = \frac{P_s}{P_I}$$

$$= \left( SINR^{-1} - SNR^{-1} \right)^{-1}$$

$$= \left( SINR^{-1} - N_s \left( R_c N_b \frac{E_b}{N_0} \right)^{-1} \right)^{-1}$$

(3.23)

3.8 Summary and conclusions

A detailed description of the EDGE system and channel model used for the simulation is presented in this chapter. High order statistical properties of the fading simulator are obtained with a good match to the theoretical results as shown. The channel estimation and synchronization involving the LS is reviewed. Finally, the channel parameters used in the simulator for evaluating the performance of the receiver are defined and rationalized.
Chapter 4

Reduced Complexity Equalizer for EDGE

4.1 Introduction

In Chapter 1 the problems of implementing optimum equalization in EDGE has been defined. In this chapter the technique of reducing the number of trellis states required to approximate the performance to the optimum is addressed. First the 8 state DDFSE is shown to be capable of equalization in EDGE. Using the concept of set-partitioning, the complexity is further reduced to 4 and 2 states with RSSE while the 8 state scheme performance is shown to be identical to the 8 state DDFSE. Due to the bi-directional equalization requirement, the backward equalizer has to operate in the negative time direction. However, a simple manipulation on the state definition has been introduced to facilitate the backward operation such that same branch metric calculation can be used by both forward and backward process. In order to ensure good performance of the reduced state algorithms, the pre-filter is introduced prior to equalization, but results in additional computational complexity. An efficient pre-filter design that exploits parallelism is proposed in this chapter. Combining the pre-filter and RSSE, a basic equalizer structure is established and is then shown by means of simulation to posses the capability to equalize over the typical GSM channels. The effects of pre-filter complexity on the performance of RSSE are also investigated.
4.2 DDFSE Algorithm

The DDFSE [44] is essentially a VA that uses the decision feedback mechanism on a per-survivor basis to approximate the MLSE using a smaller trellis, so as to achieve complexity reduction.

At the pre-filter output, the system as shown in figure 3.1 can be viewed as an ISI channel given by

\[ v_k = \sum_{n=0}^{\mu} h_n x_{k-n} + \bar{v}_{k-\mu-1} + n_k \]  \hspace{1cm} (4.1)

where \( \{\tilde{h}\}_{i=0}^{L} \) is the TOCIR of \((L + 1)\) taps that are obtained using (4.22,4.24) while \( \{v_i\} \) represent the effects of the remaining TOCIR:

\[ \bar{v}_k^+ = \sum_{i=0}^{L-\mu-1} h_{i+\mu+1} x_{k-i} \]  \hspace{1cm} (4.2)

The DDFSE consists of a MLSE that handles the first \( \mu + 1 \) taps of the TOCIR \( \{\tilde{h}_i\}_{i=0}^{L} \) while the remaining post-cursors \( \{\hat{h}_i\}_{i=\mu+1}^{L} \) are cancelled by delayed tentative decisions for each state. The channel state \( s_k' \Delta (x_{k-1}, \ldots, x_{k-\mu}, x_{k-\mu-1}, \ldots, x_{k-L}) \) can then be decomposed into

\[ s_k' = (s_k, p_k) \]  \hspace{1cm} (4.3)

\[ = ((x_{k-1}, \ldots, x_{k-\mu}), (x_{k-\mu-1}, \ldots, x_{k-L})) \]  \hspace{1cm} (4.4)

Therefore, the channel state is reduced to a hyperstate \( s_k \) with a complexity of \( Z = M^\mu \) and a partial state \( p_k \) that is handled by decision feedback. At epoch \( k \), the branch metric associated with the transition \( (s_k \rightarrow s_{k+1}) \) can be expressed as

\[ e(s_k \rightarrow s_{k+1}) = B[\bar{v}_k; x_k; \{\tilde{h}\}_{i=0}^{L}; (s_k = (x_{k-1}, \ldots, x_{k-\mu}), p_k = (x_{k-\mu-1}, \ldots, x_{k-L}))] \]

\[ = \left| \bar{v}_k - \tilde{h}_0 x_k (s_k \rightarrow s_{k+1}) - \sum_{i=1}^{\mu} \tilde{h}_i x_{k-i} (s_k) - \bar{v}_k^+ \right|^2 \]  \hspace{1cm} (4.5)

where the function \( B[\cdot] \) computes the Euclidean branch metric. The forward state transition can be expressed in the negative time direction by manipulating the channel state in (4.3) as shown:

\[ B[\bar{v}_k; x_{k-L}; (s_k = (x_{k-L+1}, \ldots, x_{k-\mu-1}), p_k = (x_{k-\mu}, \ldots, x_{k}))] = \]

\[ B[\bar{v}_k; x_{k-L}; (s_k = (x_{k-L+1}, \ldots, x_{k-\mu-1}), p_k = (x_{k-\mu}, \ldots, x_{k}))] \]  \hspace{1cm} (4.6)
4.2. DDFSE Algorithm

Rewriting (4.6),

\[ B[\bar{v}_k; x_k, \{\bar{h}_i\}_{l=0}^{L}; (s_k = (x_{k-1}, \ldots, x_{k-\mu}), p_k = (x_{k-\mu-1}, \ldots, x_{k-L}))] = \]

\[ B[\bar{v}_{k+L}; x_k, \{\bar{h}_i\}_{l=0}^{L}; (s_k = (x_{k+1}, \ldots, x_{k+\mu}), p_k = (x_{k+\mu+1}, \ldots, x_{k+L}))] \]  

(4.7)

The state \( (s_k = (x_{k+1}, \ldots, x_{k+\mu}), p_k = (x_{k+\mu+1}, \ldots, x_{k+L})) \) can be used to initialize the DDFSE for negative time operation. However, the backward equalization can be carried out in the positive time direction using the same branch metric in (4.5). In order to facilitate backward equalization in the positive time direction, the backward pre-filtered sequence and the TOCIR (maximum phase response) have to be time reversed as shown:

\[ \bar{v}_k = v_{N_B-k-L+1}, \quad 1 \leq k \leq N_B \]  

(4.8)

\[ \bar{h}_i = b_{L-i}, \quad 0 \leq i < L \]  

(4.9)

After time reversal, the channel state now follows the definition in (4.3). Since \( b_k \) has a maximum phase response, minimum phase is obtained with the time reversal process and therefore the branch metric is still optimum for the MLSE part.

4.2.1 Performance of DDFSE over the AWGN channel

In EDGE, due to the LGMSK filtering, ISI is present even without multi-path components. Figure 4.1 shows the BER of DDFSE with various filtering options over the AWGN channel. Two DDFSE schemes are evaluated:

- \( \mu = 1 \), i.e. \( Z = 8 \) denoted as 8DDFSE
- \( \mu = 2 \), i.e. \( z = 64 \) denoted as 64DDFSE

Consider the 8-PSK system with Root Raised Cosine (SRC) with roll-off of 0.5 over a AWGN channel, the degradation in performance for 64 state DDFSE when compared to the MF is negligible while for 8-DDFSE only 0.1dB worse at most. This result suggests that the proposed scheme approximates the optimum performance. With LGMSK filtering, about 1.0dB degradation is observed when compared to SRC filtering. At low
4.2. DDFSE Algorithm

\( \frac{E_b}{N_0} \) where the effects of AWGN dominates, both the DDFSEs suffer similarly due to error-propagation in the decision feedback mechanism. However, on approaching high \( \frac{E_b}{N_0} \) the effects of ISI dominates and therefore the 64DDFSE performs better than the 8DDFSE. For complexity reduction the 8DDFSE seems to be a good choice \([9,16,19]\).

![Figure 4.1: BER Performance of DDFSE with LGMSK under AWGN](image)

### 4.2.2 Performance of 8 state DDFSE over Multi-path Channel

Figure 4.2 displays exclusively the effects of ISI caused by multi-path channels on the 8 state DDFSE. The GSM channels, as described in chapter 3, are used but with the exception that the effects of time-selective fading and diversity effects are being suppressed. This is ensured by \( \sum_{i=0}^{L} |h_i|^2 = 1.0 \). The RA channel, which consists of only one effective path, therefore has a performance that is very close to the AWGN case as shown. Since the pre-filter is not inserted, the OCIR is not minimum phase for the rest of the channel profiles and degradation is expected. The worst performance is experienced in the EQ channel which represents the worst ISI condition followed by TU and HT.
4.3 RSSE Algorithm

With RSSE, further reduction in the trellis size can be achieved using the Ungerboeck set partitioning method \[45,52\] as shown in figure 4.3. For each tap delay \(i, 0 \leq i \leq L\), the signal constellation is partitioned into to \(J_i\), \(1 \leq J_i \leq M\) subsets such that \(J_1 \geq J_2 \cdots \geq J_L, 1 \leq i \leq L\). The number of trellis states required by RSSE \[45\] is

\[
Z = \prod_{i=1}^{L} J_i \tag{4.10}
\]

The subset state \(t_k\) is therefore given by the concatenation of the respective subset numbers \(t_k = m_{k-i}, 1 \leq i \leq L\):

\[
t_k = (m_{k-1}, m_{k-2}, \ldots, m_{k-L}) \tag{4.11}
\]

The DDFSE can be shown to be a special case of RSSE when \(J_1 = J_2 = \cdots = J_\mu = M\) and \(J_{\mu+1} = J_{\mu+2} \cdots = J_L = 1\). In this case the first \(\mu\) channel values of the ISI consist of one signal point while the remaining each of the \(L - \mu\) delays consists of only one subset, which is identical to the signal constellation as shown in figure 4.3.
4.3. RSSE Algorithm

However, when \( J_1 < M \) DDFSE becomes RSSE. The subset state becomes \( t_k = (t_k^{(\mu)} = (m_1, \ldots, m_\mu), t_k^{(\mu+1)} = m_{\mu+1}, \ldots, m_L) \) and again the subset trellis is constructed based on \( \mu + 1 \) taps while the partial subset states are being handled by decisions feedback using PSP. Denoting the state transition in the reduced trellis as \( (t_k^{(\mu)} \rightarrow t_{k+1}^{(\mu)}) \) at epoch \( k \) and using (4.1), the RSSE operates using the Euclidean branch metric:

\[
e_k(t_k^{(\mu)} \rightarrow t_{k+1}^{(\mu)}) = B[\tilde{v}_k; x_k|\{\tilde{h}_i\}_{i=0}^L; (t_k^{(\mu)} = (m_{k-1}, \ldots, m_{k-\mu}), t_k^{(\mu+1)} = (m_{k-\mu-1}, \ldots, m_{k-L}))]
\]

\[
= \left| \tilde{v}_k - \tilde{h}_0 x_k (t_k^{(\mu)} \rightarrow t_{k+1}^{(\mu)}) - \sum_{i=1}^{\mu} \tilde{h}_i x_{k-i} (t_k^{(\mu)}) - \tilde{v}_{k-\mu-1}^+ \right|^2
\]  

(4.12)

There are \( M/J_1 \) parallel transitions and therefore for each subset transition, the VA select the symbols with the minimum branch metric within the subset \( m_1 \).

4.3.1 Performance of RSSE

Three RSSE schemes are evaluated:

- \( J_1 = 8, J_2 = \ldots = J_L = 1 \), i.e. \( Z = 8 \) denoted as 8RSSE
4.3. RSSE Algorithm

- \( J_1 = 4, J_2 = \cdots = J_L = 1 \), i.e. \( Z = 4 \) denoted as 4RSSE
- \( J_1 = 2, J_2 = \cdots = J_L = 1 \), i.e. \( Z = 2 \) denoted as 2RSSE

In fact the 8RSSE is the same as the 8 state DDFSE with \( \mu = 1 \). Using the assumption \( \sum_{i=0}^{L} |h_i|^2 = 1.0 \), the effects of further reducing the complexity of DDFSE to 4 and 2 states are investigated. A \( T/2 \)-spaced pre-filter is inserted before the equalizer to transform the OCIR into max/minimum phase equivalent to suit bi-directional equalization. The results, which are also presented in [17], is shown in figure 4.4. It can be seen that ISI affects the 2 state RSSE the most. In general, there is an average degradation of about 2.6dB at BER of \( 10^{-3} \) between the 8 states DDFSE and 2 states RSSE. The reason to account for the loss is due to the pre-filtering side effects. The \( T/2 \)-pre-filter may have created a minimum phase OCIR (considering that the post cursors have their zeros within the unit circle) but the poly-phase components of each OCIR may not be minimum phase, therefore using the Euclidean branch metric in (4.12) [17] for each poly-phase results in a worse performance. However, the \( T \)-spaced pre-filter is shown to perform well with the GSM channel in [9] and moreover a \( T \)-spaced system is sufficient for EDGE.

4.3.2 Performance of DDFSE and RSSE over the fast time-varying frequency selective channel

Figure 4.5a assumes a mobile speed of 100km/h for all environments, while RA250, HT100 and TU50 are assumed in figure 4.5b. In the simulation a \( T \)-spaced system is considered. Using the pre-filtering from the following section, no significant difference in performance is observed between the various states. This result was further confirmed by [19] later with theoretical analysis. In TU, the path at \( 2T \) provides beneficial diversity and thus results in the best performance, followed by RA and HT as shown in both plots. An error floor appears for TU100 at high \( \frac{E_b}{N_0} \) although similar performance is also being observed for TU50 at low to moderate \( \frac{E_b}{N_0} \). An error floor of \( 3.5 \times 10^{-2} \) is observed for RA250 due to the fast time-varying effect of the channel causing inaccurate channel estimation. The estimated channel parameters are only accurate near the centre.
4.3. RSSE Algorithm

Figure 4.4: BER Performance of RSSE over the Typical GSM Channel; (a) 8 \& 4 state RSSE, (b) 8 \& 2 state RSSE

Figure 4.5: BER Performance of 8-DDFSE, 4 and 2 RSSE over Typical GSM channels
of the burst and diverges as the start and the end of the burst are approached. For HT, the OCIR has an effective length of 8-taps but only 6-taps result from channel estimation due to the TS. In addition to the limited channel estimation, the effects of fast time-varying channel are added, which results in the irreducible error floor of $3.0 \times 10^{-2}$.

### 4.4 Pre-filter

The pre-filter has two primary objectives: Firstly, to transform the OCIR into its equivalent phase (max/minimum phase), which is essential for RSSE, to suit bi-directional equalization; secondly the pre-filter has an all-pass characteristic [8] which is essentially a WMF, but matched to the OCIR to ensure noise is still 'white' after pre-filtering.

Let $H(z)$ be the $z$-transform of the T-spaced OCIR, \( \{h_i\}_{i=0}^L \). The $z$-transform auto-correlation function of the OCIR $r_{hh}(k)$ is:

$$R_{hh}(z) = H(z)H^*(1/z^*)$$  \hspace{1cm} (4.13)

Using spectral factorization,

$$R_{hh} = G_h(z)G_h^*(1/z^*)$$  \hspace{1cm} (4.14)

where $G_h(z)$ and $G_h^*(1/z^*)$ represents the minimum and maximum phase equivalent of the OCIR in the $z$-transform domain.

$$G_h^*(1/z^*) = H(z)H^*(1/z^*)[G_h(z)]^{-1}$$  \hspace{1cm} (4.15)

$$G_h(z) = H(z)H^*(1/z^*)[G_h^*(1/z^*)]^{-1}$$  \hspace{1cm} (4.16)

(4.15) and (4.16) thus suggest that the minimum and maximum phase response can be obtained by applying suitable pre-filter prior to equalization. The $T$-spaced pre-filter for backward/forward equalization is obtained as:

$$w(z) = H^*(1/z^*)[G_h(z)]^{-1}$$  \hspace{1cm} (4.17)

$$u(z) = H^*(1/z^*)[G_h^*(1/z^*)]^{-1}$$  \hspace{1cm} (4.18)
4.4. Pre-filter

Ideally, the pre-filter has an infinite impulse response. The T-spaced pre-filter coefficients \( w_n \) and \( v_n \) can be approximated using any of the methods in [8,58,59]. The adopted approach propose the use of a forward and backward prediction error filter of order \( P \) [20] to approximate the whitening filters, \([G_h(z)]^{-1}\) and \([G_h^*(1/z^*)]^{-1}\) respectively. This method requires an initial channel estimate that is obtained from the channel estimation block and a suitable order \( P \) as the input parameters. It results in the Yule-Walker equations and it is later proposed in [8] to solve using the Levinson-Durbin algorithm. Although this is efficient computationally, the reflection coefficients at step \( j \) require the computation of the inner product between the prediction coefficients and the OCIR autocorrelation: \( \Phi_{j+1} = r_{hh} \cdot a_j^T \) and \( \Phi_{j+1} = r_{hh} \cdot a_j^T \) where \( a_j = \{1, a_j(1), \ldots, a_j(j)\}^T \) and \( a_j = \{a_j^*(j), \ldots, a_j^*(1), 1\}^T \). The Schur algorithm is proposed to avoid the inner product when calculating the reflection coefficients. This has the advantage shown in [15] that parallelism can be achieved with \( O(P) \) computing time over \( O(P) \) processors as compared to \( O(P \log_2 P) \) computing time attainable with Levinson-Durbin algorithm implemented in parallel. A similar technique from [15] is applied to obtain the prediction coefficients as shown:

Initialization:

\[
G_0 = \begin{bmatrix} g_0(0) & g_0(1) & \cdots & g_0(P) \\ g_0^R(0) & g_0^R(1) & \cdots & g_0^R(P) \end{bmatrix} = \begin{bmatrix} 0 & R_{hh}(1) & \cdots & r_{hh}(P) \\ r_{hh}(0) & R_{hh}(1) & \cdots & r_{hh}(P) \end{bmatrix} \tag{4.19}
\]

\[
A_0 = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 1 & 0 & \cdots & 0 \end{bmatrix} \tag{4.20}
\]

where \( G_j \) and \( A_j \) are the Schur and prediction coefficients matrices of order \( 2 \times (P+1) \) respectively at recursion step \( j \) and \( j = 0,1,\ldots,P-1 \).

i. The reflection coefficients \( \Gamma_{j+1, j+1}^R \) is obtained from Schur coefficients matrix as shown: \( \Gamma_1 = -\frac{g_0(1)}{g_0^R(0)} \) and \( \Gamma_1^R = \Gamma_1^*, j = 0 \)

ii. Right shift the bottom row of \( G \) by 1, update and store the result in \( G \) for the next step:

\[
\begin{bmatrix} 1 & \Gamma_1 \\ \Gamma_1^R & 1 \end{bmatrix} \begin{bmatrix} g_0(0) & g_0(1) & \cdots & g_0(P) \\ 0 & g_0^R(0) & \cdots & g_0^R(P-1) \end{bmatrix} = \begin{bmatrix} X & 0 & g_1(2) & \cdots & g_1(P) \\ X & g_1^R(1) & g_1^R(2) & \cdots & g_1^R(P) \end{bmatrix}
\]
where 'X' means Don't care.

iii. Right shift is performed on the bottom row of \( A \) by 1 with a zero inserted; Order update is performed using the reflection coefficients from (i) and store result in \( A \) for the next step as shown:

\[
\begin{bmatrix}
1 & \Gamma_1 \\
\Gamma^R_1 & 1
\end{bmatrix}
\begin{bmatrix}
1 & 0 & \ldots & 0 & 0 \\
0 & 1 & 0 & \ldots & 0
\end{bmatrix}
= 
\begin{bmatrix}
1 & \Gamma_1 & \ldots & 0 & 0 \\
\Gamma^R_1 & 1 & 0 & \ldots & 0
\end{bmatrix}
, \ j = 1
\]

The same procedure is repeated for the next recursion step:

\[
\Gamma_2 = -\frac{g_1(2)}{g_1(1)} \text{ and } \Gamma^R_2 = \Gamma^*_2 \ j = 1
\]

\[
\begin{bmatrix}
1 & \Gamma_2 \\
\Gamma^R_2 & 1
\end{bmatrix}
\begin{bmatrix}
X & 0 & g_1(2) & \ldots & g_1(P) \\
X & X & g_1^R(1) & \ldots & g_1^R(P - 1)
\end{bmatrix}
= 
\begin{bmatrix}
X & X & 0 & g_2(3) & \ldots & g_2(P) \\
X & X & g_2^R(3) & \ldots & g_2^R(P)
\end{bmatrix}
\]

\[
\begin{bmatrix}
1 & \Gamma_2 \\
\Gamma^R_2 & 1
\end{bmatrix}
\begin{bmatrix}
1 & \Gamma_1 & \ldots & 0 \\
0 & \Gamma^R_1 & 1 & \ldots & 0
\end{bmatrix}
= 
\begin{bmatrix}
1 & (\Gamma_1 + \Gamma_2 \Gamma^R_1) & \Gamma_2 & \ldots & 0 & 0 \\
\Gamma^R_2 & ( \Gamma_1 \Gamma^R_2 + \Gamma^R_1) & 1 & 0 & \ldots & 0
\end{bmatrix}
\]

Therefore,

\[
\begin{bmatrix}
1 & a_2(1) & a_2(2) & \ldots & 0 \\
a^*_2(1) & 1 & 0 & \ldots & 0
\end{bmatrix}
= 
\begin{bmatrix}
1 & (\Gamma_1 + \Gamma_2 \Gamma^R_1) & \Gamma_2 & \ldots & 0 & 0 \\
\Gamma^R_2 & ( \Gamma_1 \Gamma^R_2 + \Gamma^R_1) & 1 & 0 & \ldots & 0
\end{bmatrix}
\]

The vectors \( a_j \) and \( a^R_j \) are then obtained with respect to each pair of reflection coefficients at each recursion. Each computation step is accomplished by a right shift, multiply, accumulate and store operation. The subsequent recursion thus becomes straightforward with procedure (i) to (iii) and for each recursion step \( j = p, \)

\[
G_p = 
\begin{bmatrix}
X & \ldots & X & 0 & g_p(p + 1) & \ldots & g_p(P) \\
X & \ldots & X & g^R_p(p) & g^R_p(p + 1) & \ldots & g^R_p(P)
\end{bmatrix}
\]

\[
A_p = 
\begin{bmatrix}
1 & a_p(1) & \ldots & \Gamma_p & 0 & \ldots & 0 \\
\Gamma^R_p & \ldots & a^R_p(1) & 1 & 0 & \ldots & 0
\end{bmatrix}
\]

The recursion is summarized as shown:

a. Compute reflection coefficients

\[
\Gamma_{p+1} = -\frac{g_{p+1}}{g^R_p(p)} \text{ and } \Gamma^R_{p+1} = \Gamma^*_p
\]

b. Update \( G \)
4.4. Pre-filter

\[
\begin{bmatrix}
1 & \Gamma_{p+1} \\
\Gamma_{p+1}^R & 1
\end{bmatrix}
\begin{bmatrix}
X & \ldots & X & 0 & g_p(p+1) & \ldots & g_p(P) \\
X & \ldots & X & g_p^R(p) & \ldots & g_p^R(P-1)
\end{bmatrix}
\]

\[
\begin{bmatrix}
X & \ldots & X & 0 & g_{p+1}(p+2) & \ldots & g_{p+1}(P) \\
X & \ldots & X & g_{p+1}^R(p+2) & \ldots & g_{p+1}^R(P-1)
\end{bmatrix}
\]

c. Update A

\[
\begin{bmatrix}
1 & \Gamma_{p+1} \\
\Gamma_{p+1}^R & 1
\end{bmatrix}
\begin{bmatrix}
1 & a_p(1) & \ldots & \Gamma_p & 0 & \ldots & 0 \\
0 & \Gamma_p^R & \ldots & a_p^*(p-1) & 1 & 0
\end{bmatrix}
\]

\[
\begin{bmatrix}
1 & a_{p+1}(1) & \ldots & \Gamma_{p+1} & 0 & \ldots & 0 \\
\Gamma_{p+1}^R & \ldots & a_{p+1}^*(1) & 1 & 0 & \ldots & 0
\end{bmatrix}
\]

The procedure is repeated until the prediction coefficients of order \(P\) are reached. Using (4.17,4.18) the pre-filter coefficients are obtained. The corresponding \(T\)-spaced TOCIR are:

\[
f_n^- = \begin{cases}
\sum_{l=0}^{n} h_{n-l}u_l & 0 \leq n \leq L \\
\sum_{l=n-L}^{n} h_{n-l}u_l & 0 < n < (P + L)
\end{cases}
\]  
(4.21)

\[
f_n = \sum_{l=n-L}^{P+L} h_{n-l}u_l & n = (P + L), \ldots, (P + 2L)
\]  
(4.22)

\[
b_n^+ = \begin{cases}
\sum_{l=n}^{P+L} h_{n-l}w_l & (P + L) \leq n \leq (P + 2L) \\
\sum_{l=n-L}^{n} h_{n-l}w_l & L < n < (P + L)
\end{cases}
\]  
(4.23)

\[
b_n = \sum_{l=0}^{n} h_{n-l}w_l & n = 0, \ldots, L
\]  
(4.24)

where \(f_n, b_n\) are the minimum/maximum phase equivalent required by the RSSE and \(f_n^-, b_n^+\) are the pre/post cursors residual of the TOCIR that can be reduced by increasing the order of the PEF. Consequently, the \(k^{th}\) symbol output of the pre-filter can be expressed as in (4.1).
4.4. Pre-filter

4.4.1 Pre-filtering Effects with Dispersive Channels

Among the GSM channels, the EQ has the worst dispersion. Figure 4.6a and b shows a snapshot the EQ channel estimated by the LS method and its equivalent down-sampled version at rate $1/T$ respectively. Two sets of PEF of order $P = 10$ and $P = 25$ are considered. The order $P$ PEF for a $L+1$ tap channel thus results in a $(P + L + 1)$ taps pre-filter, i.e. 16 and 31 taps as shown in figure 4.7a, b and 4.7c, d respectively. Similar characteristics are obtained for $P = 25$ as shown in figure 4.8. It should be noted that the forward pre-filter has an anti-causal response and in this case a delay of $(P + L)$ is introduced.

After pre-filtering, a TOCIR of $P + 2L + 1$ taps is seen by the trellis equalizer, i.e. 21 and 36 taps as in figure 4.9 and 4.10 respectively. The finite-length pre-filters are such that $\sum_{i=0}^{P+2L} |f_i|^2 = 1$ and $\sum_{i=0}^{P+2L} |b_i|^2 = 1$. As the order $P \rightarrow \infty$ the pre-filter approaches the ideal all-pass filter that has an IIR response, but the proposed method attempt to approximate the ideal with an FIR. This results in the residual pre-cursors.

![Figure 4.6: Estimated EQ50 channel](image)
Figure 4.7: Forward and Backward pre-filter for Estimated EQ50 channel, $P = 10$

Figure 4.8: Forward and Backward pre-filter for Estimated EQ50 channel, $P = 25$
4.4. Pre-filter

Figure 4.9: Min/Maximum phase equivalent of Estimated EQ50 Channel, P=10

as shown in figure 4.9. The residual pre-cursors can be reduced with a higher order FIR as illustrated in figure 4.10.

The residual pre-cursors have an impact on the BER as in shown figure 4.11. This is because only the post-cursors are used by DDFSE and RSSE to compute the most likely sequence. Considering the 8DDFSE, best BER performance is achieved with $P = 30$ at a cost of higher computational complexity. Negligible degradation is observed when compared to $P = 25$. The worst performance is obtained with order $P = 10$. This is due to the effects of residual pre-cursor as shown in 4.9. Due to the severe dispersion in EQ channel, the 2-RSSE when compared to 4-RSSE is more sensitive to the order of the PEF.

4.4.2 Pre-filtering Effects with Long Channel Impulse Response

It seems from the previous findings and also in [8] that $P = 25$ is sufficient for the highly dispersive EQ channel. However, lower order PEF are still preferred for complexity
4.4. Pre-filter

Figure 4.10: Min/Maximum phase equivalent of Estimated EQ50 Channel, P=25

Figure 4.11: Effects of pre-filtering on the performance of RSSE over EQ50
4.4. Pre-filter

reduction, and moreover the EQ channel is somewhat an unrealistic scenario. Figure 4.12 shows a snapshot of the HT100 channel which has the longest OCIR. The HT100 channel has a small echo near 5T and is represented by a 8-tap FIR even though only 6-tap results from the channel estimation. The \( P = 10 \) is assumed and the pre-filter coefficients are obtained and shown in figure 4.13.

A minimum phase TOCIR of \((P + 2L + 1)\) taps is created by the pre-filter, i.e. 21 taps as shown in figure 4.14a. However, only the last \((L + 1)\) i.e 6 taps are used by the trellis equalizer and there are no noticeable residual pre-cursors. Similar characteristics is observed in 4.14b. where a maximum phase TOCIR is created and only the first 6 taps are used by the equalizer.

In figure 4.5 the \( P = 10 \) is assumed for all channel environments and in particular for HT100, and no sign of performance degradation is observed for various reduced trellis schemes. This is observed even for the dispersive TU50 channel. This result suggests that the \( P = 10 \) is sufficient for equalization in EDGE, for all channel conditions.

![Figure 4.12: Estimated HT100 channel](image)
4.4. Pre-filter

Figure 4.13: Forward and Backward Pre-filter for Estimated HT100 channel

Figure 4.14: Minimum and Maximum phase equivalent of Estimated HT100 Channel
4.5 Conclusions

In this chapter the 8-DDFSE is shown to have a performance that is close to the optimum over the AWGN channel. Additionally, two more possible schemes that involves the RSSE are formulated and are shown to be capable of reducing the complexity to 4 and 2 states. In order to ensure the good performance of the reduced state algorithms, a pre-filter is essential prior to the DDFSE and RSSE. An efficient pre-filter coefficient computation method based on the Schur algorithm, that exploits parallelism, is proposed. The higher the order of the PEF better approximates the ideal at a higher cost of complexity. For complexity reduction, a 10th order PEF is capable of coping with dispersive channels as in the urban environment, channel with long impulse responses as in hilly terrain and last but not least the rural area. Finally, an equalization scheme that consists of the pre-filter and RSSE is presented and is shown to be capable of good equalization over the typical GSM channel. The application of these techniques to EDGE had not previously been published prior to this work [16–18]
Chapter 5

Soft-Output Equalization for EDGE

5.1 Introduction

This chapter investigates the issues of reduced trellis on the soft output equalization for EDGE. Two types of Soft-In/Soft-out algorithms are being investigated. First, the BCJR type MAP algorithm in the logarithm domain is incorporated into the equalizer structure derived in chapter 4 and results in the 8 states SO-DDFSE. A much simpler technique involving the SSA and DDFSE is introduced. It computes the soft outputs using forward recursion and without noise variance estimation. For further complexity reduction, set-partitioning is applied to the SO-DDFSE which results in a scheme involving the RSSE that has a modest complexity of 4 and 2 trellis states. However, these proposed methods make the 'white' Gaussian assumption regarding the perturbation noise, which is undermined in a interference limited environment. In addition, these reduced trellis schemes suffer from decision feedback errors and inaccurate noise variance estimation error (for Log-MAP). As a result an improved scheme involving the RSSE and Log-MAP in cascade is proposed resulting in the Cascaded Soft-output RSSE (CSO-RSSE). A similar technique that requires only forward recursion is reported in [23], is shown to outperform the single stage (SO-DDFSE) in [21]. However, it employs the DDFSE in cascade with Lee's algorithm [22], where the soft outputs
are delivered in the probability domain and requires division operations, which require more computation effort than a multiplication. The proposed method has lower complexity and avoids the drawback of probability domain implementation and is shown to outperform the single stage schemes.

5.2 Soft-In/Soft-Out Algorithms for Equalization

Two types of Soft-In/Soft-Out (SISO) algorithms, the BCJR MAP [67] and the SSA [13] are considered for equalization in EDGE. The SSA offers a much simpler solution than BCJR-MAP but at the expense of sacrificing some optimality. However, it requires only forward recursion to compute the soft outputs without the need of noise variance, which is essential in BCJR-MAP.

Figure 5.1 shows a simplified channel model of the EDGE communication in figure 3.1. The goal of the considered SISO is to estimate the a posteriori Log Likelihood Ratio (LLR) of each constituent bit in the symbol \( x_k = F(b_{k,0}, b_{k,1}, b_{k,2}) \) as follows

\[
\Lambda(b_{k,i}) = \ln \frac{P_r(b_{k,i} = 1 | \bar{v}_i^K)}{P_r(b_{k,i} = 0 | \bar{v}_i^K)}, \quad i = 0, \ldots, N_b - 1
\]

where \( N_b \) is the number of bits per symbol, \( \bar{v}_i^K = \{\bar{v}_1, \ldots, \bar{v}_K\} \) is observed sequence of length \( K \) at the output of the pre-filter. However, the symbol APP, \( P_r(x_k^{(j)} | \bar{v}_i^K) \) is estimated by the soft equalizer. Using Bayes' rule

\[
P_r(x_k^{(j)} | \bar{v}_i^K) = \frac{p(\bar{v}_i^K | x_k^{(j)}) P_r(x_k^{(j)})}{P_r(\bar{v}_i^K)}
\]

where \( P_r(\bar{v}_i^K | x_k^{(j)}) \) is the conditional probability of the observed signal given \( x_k^{(j)} \). \( P_r(x_k^{(j)}) \) is the a priori probability of the \( j^{th} \) symbol in the signal set of size \( M \) being
transmitted at time $k$. Assuming that $x_k$ signals are equally likely the LLR $\Lambda(b_{k,i})$ can now be calculated from the a posteriori probability of the transmitted symbols as

$$\Lambda(b_{k,i}) = \ln \frac{\sum_{b_{k+1,i}=l'} \Pr(s_k^{l'}) | \tilde{v}_k^K)}{\sum_{b_{k+1,i}=0'} \Pr(s_k^{0'}) | \tilde{v}_k^K)} \quad \{ i = 0, \ldots, N_k - 1 \} \quad \{ j = 1, \ldots, M \} \quad (5.3)$$

Just as with the MLSE equalizer, the SISO requires the construction of a trellis with states corresponding to the full channel memory. The trellis size required is $Z = M^L$, for a $(L + 1)$ taps channel and $M = 8$ for 8PSK. The LLR can be obtained from the trellis as

$$\Lambda(b_{k,i}) = \ln \frac{\sum_{(l,p) \in B_1} \Pr(s_k = l; s_{k+1} = l'| \tilde{v}_k^K)}{\sum_{(l,p) \in B_0} \Pr(s_k = l; s_{k+1} = 0'| \tilde{v}_k^K)}, \quad l, l' = 0, \ldots, Z - 1 \quad (5.4)$$

where $B_1$ is the set of transitions $(l \rightarrow l')$ such that the $i^{th}$ bit of symbol $x_k$, $b_k = l'$ and vice versa $b_k = 0'$ for $B_0$.

The detection problem now reduces to finding the APP, $Pr(s_k = l; s_{k+1} = l'| \tilde{v}_k^K)$ which can be seen as the a posteriori state transition probabilities, which are known for each state transition (or branch) in the trellis.

### 5.2.1 BCJR MAP

The key of BCJR is to decompose the a posteriori transition probability for a transition at time $k$ into three separable factors [67]: the first depending only on the past observations $\tilde{v}_1^K$, the second depending on only the present observations, $\tilde{v}_k$ and the third depending only on the future observations $\tilde{v}_{k+1}^K$ as shown

$$Pr(s_k = l; s_{k+1} = l'| \tilde{v}_k^K) = Pr(s_k = l; \tilde{v}_1^{k-1}) Pr(s_{k+1} = l'| \tilde{v}_k s_k = l) Pr(\tilde{v}_{k+1}^K | s_{k+1} = l') / Pr(\tilde{v}_1^K)$$

$$= \alpha_k(l) \gamma_k(l, l') \beta_{k+1}(l') / Pr(\tilde{v}_1^K) \quad (5.5)$$

$\alpha_k(l)$ is a probability measure for state $s_k = l$ at time $k$, $\beta_{k+1}(l')$ is a probability measure for state $s_{k+1} = l'$ at time $k + 1$. Finally, $\gamma_k(l, l')$ is the branch transition probability that measure connecting state $s_k = l$ at time $k$ to $s_{k+1} = l'$ at time $k + 1$ as shown in figure 5.2. The full derivation of (5.5) is given in appendix B.
5.2. Soft-In/Soft-Out Algorithms for Equalization

5.2.1.1 BCJR Log-MAP

The BCJR MAP (5.5) requires large memory and a large number of operations involving exponentiations and multiplications as it deliver soft decisions in the probability domain [13, 14]. It computes the a posteriori information for each symbol taken into account information from all symbols in a block. To avoid number representation problem and to ease the computation requirements, the BCJR MAP is best represented in the logarithm domain as the equivalent Log-MAP [14]. First, the branch transition probability $\gamma_k$ in the logarithm domain is defined

$$\gamma_k = \ln \gamma_h (l, l')$$

$$= \ln Pr(s_{k+1} = l' ; \bar{s}_k | s_k = l)$$

$$= \ln Pr(\bar{s}_k | s_{k+1} = l' ; s_k = l) + \ln Pr(s_{k+1} = l' | s_k = l)$$

where $l, l' = 0, \cdots, M^L - 1$ and $Pr(s_{k+1} = l' | s_k = l)$ is the a priori extrinsic information.

The first term in (5.6) can be computed using the model in figure 5.1 as

$$\gamma_k (l, l') = - \frac{1}{2\sigma_n^2} |\bar{u}_k - \bar{h}_k x_k (l, l')|^2 +$$

$$\ln Pr(s_{k+1} = l' | s_k = l) + C$$

\[ (\gamma_k (l, l')) \]
5.2. Soft-In/Soft-Out Algorithms for Equalization

where \( C = \ln \left( \frac{1}{2\sigma^2} \right) \). The output of the BCJR Log-MAP is

\[
\Lambda(b_{k,i}) = \ln \sum_{(l \mapsto l') \in \mathbb{B}^1} e^{(\overline{\alpha}_k(l) + \overline{\eta}(l,l') + \overline{\beta}_{k+1}(l'))} - \ln \sum_{(l \mapsto l') \in \mathbb{B}^0} e^{(\overline{\alpha}_k(l) + \overline{\eta}(l,l') + \overline{\beta}_{k+1}(l'))}
\]

(5.8)

where \( \overline{\alpha}_k(l) \triangleq \ln \alpha_k(l) \) and \( \overline{\beta}_k(l) \triangleq \ln \beta_k(l) \) are the forward and backward recursion respectively updated as follows

\[
\overline{\alpha}_k(l) = \ln \sum_{l' = 0}^{Z-1} e^{(\overline{\alpha}_{k-1}(l') + \overline{\eta}_{k-1}(l',l))}
\]

(5.9)

\[
\overline{\beta}_k(l) = \ln \sum_{l' = 0}^{Z-1} e^{(\overline{\beta}_{k+1}(l') + \overline{\eta}_k(l,l'))}
\]

(5.10)

The equations (5.8) to (5.10) can be evaluated exactly using the Jacobian logarithm [14]:

\[
\ln(e^{\delta_1} + e^{\delta_2}) = \max(\delta_1, \delta_2) + f_c(|\delta_1 - \delta_2|)
\]

(5.11)

where the correction term

\[
f_c(|\delta_1 - \delta_2|) = \ln(1 + e^{-|\delta_1 - \delta_2|})
\]

(5.12)

can be implemented using a lookup table. The correction factor \( f_c(\cdot) \) is close to zero when \( \delta_1 \) and \( \delta_2 \) are dissimilar. The expression \( \ln(e^{\delta_1} + \cdots + e^{\delta_n}) \) marginalize the probabilities \( \delta_n \), i.e. sum of probabilities, in the logarithmic domain. It is computed exactly recursively using the marginalization operator, \( \max^* \), using (5.11) as follows

\[
\max^* \delta_i = \ln(e^{\delta_1} + \cdots + e^{\delta_n})
\]

\[
= \ln(\Delta + e^{\delta_n}), \quad \Delta = e^{\delta_1} + \cdots + e^{\delta_{n-1}} = e^{\delta}
\]

\[
= \max(\ln \delta, \delta_n) + f_c(\ln \Delta - \delta_n)
\]

\[
= \max(\delta, \delta_n) + f_c(\delta - \delta_n)
\]

(5.13)

The recursive procedure in (5.13) can be applied to evaluating \( \Lambda(b_{k,i}) \) in (5.8), where

\[
\delta_n = \ln \alpha_k(n) + \ln \gamma_k(n,n') + \ln \beta_{k+1}(n'), \quad n, n' = 0, 1, \cdots, Z - 1
\]

(5.14)

Since the channel is of feed-forward nature, the soft-output of BCJR Log-MAP in (5.8) can be expressed as

\[
\Lambda(b_{k,i}) = \max^* \{ \ln \alpha_k(l) + \ln \gamma_k(l, l') + \ln \beta_{k+1}(l') \} - \max^* \{ \ln \alpha_k(l) + \ln \beta_k(l) \}, \quad i = 0, \cdots, N_y - 1
\]

(5.15)
5.2. Soft-In/Soft-Out Algorithms for Equalization

5.2.1.2 BCJR Max-Log-MAP

The BCJR Max-Log-MAP can be approximated by disregarding the correction term [14] in (5.11) when evaluating (5.8), (5.9) and (5.10) as shown

\[ \ln(e^{\delta_1} + \cdots + e^{\delta_n}) \approx \max_{i \in \{1, \ldots, n\}} \delta_i \]  (5.16)

where \( \max_{i \in \{1, \ldots, n\}} \delta_i \) can be computed successively calculating \((n-1)\) maximum functions over only two values. Hence the soft output of Max-Log-MAP is

\[ \Lambda(b_{k,i}) = \max_{(l|b_{k,i} = 0')} (\overline{\alpha}_k(l) + \overline{\beta}_k(l)) - \max_{(l|b_{k,i} = 0')} (\overline{\alpha}_k(l) + \overline{\beta}_k(l)), \quad i = 0 \cdots, N_b - 1 \]  (5.17)

\[ \overline{\alpha}_k(l) = \max_{l'}(\overline{\alpha}_{k-1}(l') + \overline{\gamma}_{k-1}(l', l)), \quad l' = 0, \cdots, Z - 1 \]  (5.18)

\[ \overline{\beta}_k(l) = \max_{l'}(\overline{\beta}_{k+1}(l') + \overline{\gamma}_{k}(l, l')), \quad l' = 0, \cdots, Z - 1 \]  (5.19)

The computations of \( \overline{\alpha}_k(l) \) and \( \overline{\beta}_k(l) \) in (5.18) and (5.19) is equivalent to the computation of the path metric in the forward and backward recursions, respectively, in the VA, with branch metric \( \overline{\gamma}_k(l, l') \), as multiplications are replaced by add operations, which are the same as the Add-Compare-Select (ACS) operations in VA [13].

5.2.2 SSA

The APP in (5.2) can be estimated under the constraints of a fixed decision delays [13], \( D \geq L \) as \( Pr(x_{k-D}^{(j)}|\tilde{v}_1^k) \) or its joint probability equivalent \( Pr(x_{k-D}^{(j)}; \tilde{v}_1^k) \) where \( j = 1, \cdots, M \) and \( \tilde{v}_1^k = \{\tilde{v}_1, \cdots, \tilde{v}_k\} \) is the received sample from time 1 to \( k \). In general for arbitrary \( \delta \), the probability, \( Pr(x_{k-\delta}; \tilde{v}_1^k) \) can be re-written using the Bayes rule [13] as

\[ Pr(x_{k-\delta}; \tilde{v}_1^k) = \sum_{s_{k+1}} Pr(x_{k-\delta}|s_{k+1}, \tilde{v}_1^k)Pr(s_{k+1}; \tilde{v}_1^k) \]  (5.20)

and

\[ Pr(s_{k+1}; \tilde{v}_1^k) = \sum_{s_k \in \mathcal{Q}} Pr(s_k; \tilde{v}_1^{k-1})Pr(s_{k+1}; \tilde{v}_k|s_k) \]  (5.21)

where \( \mathcal{Q} \) is the set of \( M \) state s of \( s_k \) connecting to \( s_{k+1} \). It can seen in (5.21) that the computation is performed in the probability domain and requires knowledge of noise
5.2. Soft-In/Soft-Out Algorithms for Equalization

variance. These are avoided in SSA by carefully manipulating the second term in (5.21) which is essentially the branch transition probability in (5.6). Denoting the Additive Branch Metric (ABM), \( \hat{\gamma}_k = \ln \gamma_k \) during the transition \( \zeta_k = (s_k \rightarrow s_{k+1}) \), \( \hat{\gamma}_k \) can be scaled such that

\[
\hat{\gamma}_k(\zeta_k) = -C_1 \ln Pr(s_{k+1} = l'; \bar{\nu}_k| s_k = l) + C_2
\]  

(5.22)

where are \( C_1, C_2 \) are arbitrary constants. Assuming the perturbation is AWGN and the a priori probability \( Pr(s_{k+1} = l'| s_k = l) \) remains constant, the ABM reduces to

\[
\hat{\gamma}_k(\zeta_k) = |\bar{\nu}_k - \sum_{i=0}^{L} \bar{h}_i x_{k-i}|^2
\]  

(5.23)

where \( C_2 = C_1 \ln \left( \frac{1}{2\pi\sigma^2_n} Pr(s_{k+1}| s_k) \right) \) and \( C_1 = 2 \sigma_n^2 \). Hence, the ABM does not depend on the noise variance. For any path, \( \pi_k \triangleq (\zeta_1, \ldots, \zeta_k) = (x_1, \ldots, x_{k-1}, x_{k+1}) \) in the trellis diagram and given that the initial state \( s_1 \) is known,

\[
Pr(\pi_k, \bar{\nu}_1^k) = Pr(\pi_k, \bar{\nu}_1^k| s_1)
\]  

(5.24)

since the Additive Path Metric (APM) of a path \( \pi_k \) is the sum of related ABM and therefore

\[
\hat{\gamma}_k(\pi_k) = \sum_{i=1}^{k} \hat{\gamma}_i(\zeta_i) = -C_1 \ln Pr(\pi_k, \bar{\nu}_1^k) + kC_2
\]  

(5.25)

The APM thus provides a measure of the likelihood that the path \( \pi_k \) has been actually transmitted. The essence of SSA is that these paths at time \( k \) are divided into \( M \) exclusive subsets

\[
\Delta_k(\delta, j) \triangleq \{ \pi_k | \bar{\nu}_k^{(j)} \}, \quad j = 1, \ldots, M
\]  

(5.26)

The transmitted path belongs to one and only one of the subsets \( \Delta_k(\delta, j) \). Instead of taking into consideration all paths belonging to subset \( \Delta_k(\delta, j) \) to estimate the APP that an optimal algorithm will perform, the SSA selects the path with the minimum APM. For a decision delay \( D \), the SSA computes the soft output as

\[
\min_{\pi_k \in \Delta_k(D,j)} (\hat{\gamma}_k(\pi_k)), \quad j = 1, \ldots, M
\]  

(5.27)
Similar to the VA, the SSA [13] stores for each state $s_k$ a soft survivor matrix $\Xi(s_k)$ such that
\[
\Xi(s_k) \triangleq [\xi_{i,j}(s_k)]
\]
\[
= [\chi(s_k, x_{k-L-i}^{(j)})] \quad \text{for } i = 1, \ldots, D - L, \quad j = 1, \ldots, M
\]
where $D \geq L$ is the fixed decision delay, the $i$th row consists of $M$ augmented survivor metrics $\chi(s_k, x_{k-L-i}^{(j)})$, which can be updated as follows:
\[
\chi(s_{k+1}, x_{k-L}) = \chi(s_k) + \gamma_k(\zeta_k)
\]
\[
\chi(s_{k+1}, x_{k-\delta}) = \min_{\delta} (\chi(s_k, x_{k-\delta}) + \gamma_k(\zeta_k)), \quad L < \delta \leq D
\]
\[
\chi(s_{k+1}) = \min_{s_k} (\chi(s_k) + \gamma_k(\zeta_k))
\]
where the survivor metric, $\chi(s_k) \triangleq \min(\gamma(\pi_k)|x_k)$. The soft output of SSA can be obtained from the last row of $\Xi(s_k)$
\[
\min_{\pi_k \in \Delta_k(D,j)} (\gamma_k(\pi_k)) = \min_{s_k+1} (\xi_{D-L,j}(s_{k+1})), \quad j = 1, \ldots, M
\]
\[
= \min_{s_k+1} (\chi(s_{k+1}, x_{k-D}^{(j)})) \quad j = 1, \ldots, M
\]
The rows of $\Xi(s_k)$ are shifted by one and the first row is filled with (5.29) and using (5.4) the soft bits are computed.

Comparing the BCJR MAP variants and SSA algorithm, the BCJR MAP requires buffering of the forward recursion while computing the backward recursion. The SSA estimates the soft output using forward recursion under the constraint of a delay, $D$, which requires a smaller soft survivor matrix as in (5.28). This also suggest that the complexity of SSA is dependent on the decision delay, $D$. Referring to the complexity analysis in section 6.5.2, both the BCJR MAP variants requires a storage 18 times as much as the SSA (with $D = 5L$) but requires 11 times less computation than the SSA. However, when $D = L$, the SSA requires 3 less the computation effort than the BCJR MAP, but at the expense of not more than 1.0 dB loss in most environments as seen in figure 5.4 to 5.6.
5.3 Reduced Complexity SISOs

Due to the trellis nature, these soft-output schemes are complex for implementation in EDGE as their trellis size is dependent on the symbol size and the length of channel memory and reduced complexity equivalents are necessary. One common feature of these algorithms is that they share a similar trellis structure.

5.3.1 Trellis Reduction with DDFSE

As shown in figure 5.3, the DDFSE can be applied to estimate the full trellis by a smaller trellis such that the first part of the estimated channel \( \{ \hat{h}_i \}_{i=0}^L \) is handled by the MLSE via the VA while the remaining post-cursor \( \{ \hat{h}_i \}_{i=\mu+1}^L \) are cancelled by the delayed tentative decisions for each state on per survivor basis. At each stage of the trellis, the branch transition probability, \( \gamma_k \), are calculated using the fully hypothesized MLSE symbols as well as tentative decisions (for each of the \( M^\mu \) survivor paths) on past transmitted symbols corresponding to the DFE taps. That is (5.7) is replaced
5.3. Reduced Complexity SISOs

with

\[ \bar{\eta}_k(l', l) = \ln \text{Pr}(s_{k+1} = l|s_k = l') + C \]
\[ - \frac{1}{2\sigma_n^2} \left| \tilde{v}_l - \tilde{h}_0 x_k(s_k \rightarrow s_{k+1}) - \sum_{i=1}^{\mu} \tilde{h}_i x_{k-i}(s_k) - \sum_{i=0}^{L-\mu-1} \tilde{h}_{i+\mu+1} x'_{k-\mu-1-i} \right|^2 \]

(5.34)

where \( x'_k \) are the tentative decisions associated with the current state, \( s_k \) which are inherited from the previous state having the largest path metric.

**SO-DDFSE**

The branch transition probability can be simplified by disregarding the first two terms in (5.34). Both are constant terms and will cancel in the numerator and denominator of \( \Lambda(b_{k;i}) \) in (5.4) and moreover, the extrinsic a priori probability, \( \text{Pr}(s_{k+1}|s_k) \) is a constant in the current application. However, the noise variance, \( \sigma_n^2 \) remains as part of the expression since it directly affects the overall result. Hence the branch metric for BCJR Log-MAP can be obtained as

\[ \bar{\eta}_k(l) \propto - \frac{1}{2\sigma_n^2} \left| \tilde{v}_l - \tilde{h}_0 x_k(s_k \rightarrow s_{k+1}) - \sum_{i=1}^{\mu} \tilde{h}_i x_{k-i}(s_k) - \sum_{i=0}^{L-\mu-1} \tilde{h}_{i+\mu+1} x'_{k-\mu-1-i} \right|^2 \]

(5.35)

The expression is used for computing the LLR and updating the forward and backward recursions in (5.8) to (5.10). Similarly, the expression can be applied to (5.17) to (5.19) for Max-Log-MAP. It should be noted that the noise variance is no longer required in this case due to the max operation used in selecting paths.

**RS-SSA**

Similarly, the DDFSE can be directly applied to the full state SSA. The branch transition probability in (5.22) after scaling is

\[ \bar{\eta}_k(l) = \left| \tilde{v}_l - \tilde{h}_0 x_k(s_k \rightarrow s_{k+1}) - \sum_{i=1}^{\mu} \tilde{h}_i x_{k-i}(s_k) - \sum_{i=0}^{L-\mu-1} \tilde{h}_{i+\mu+1} x'_{k-\mu-1-i} \right|^2 \]

(5.36)

As before, using (5.29) to (5.31) the augmented survivor metrics are updated and the soft output of SSA is obtained from (5.32). The only difference to the full state SSA is that the reduced state SSA stores for each state, \( s_k \in M^\mu \), a survivor matrix \( X_i(s_k) \).
5.3. Reduced Complexity SISOS

Finally, the APP bits are obtained from (5.4). It is worth noting that the SSA estimates the APP forwardly but under the constraint of a fixed delay $D$, and does not require the knowledge of noise variance as shown in (5.36).

5.3.2 Performance of Soft output DDFSE Equalization over Typical GSM channels

The performance of SO-DDFSE (Log-MAP and Max-Log-MAP) and RS-SSA are evaluated for the EDGE system as shown in figure 1. The receiver performance using MCS-5 mode is studied as similar results can be extended to other MCS modes. The channel model considered here is the multi-path fading channel with the GSM typical profiles RA250, TU50 and HT100. The perturbations assumed that the simulation includes the effects of thermal noise (AWGN), the receive front end filter as mentioned in chapter 3 and the pre-filter from chapter 4.

In figure 5.4 to 5.6, the reduced state soft output schemes, SO-DDFSE and RS-SSA, using the 8 state DDFSE ($\mu = 1$) in section 4.2.1, are shown to be sufficient for equalization for EDGE. In all the three channels, the improvement is a coding gain greater than 3dB at $10^{-2}$ BER with respect to the hard decision DDFSE. SSA of different decision delay $D = \mu$ and $D = 5\mu$ are also presented and no significant improvement is obtained with a higher delay as the SSA operates on the hyperstate instead of the channel state. The Max-Log-MAP and the SSA are less than 0.5 dB and 1.0 dB worse respectively when compared to the Log-MAP at 1% BER.

In figure 5.4 the channel degradation is mainly due to severe Doppler effect, the coding gains of soft output algorithms are higher than those in TU50 and HT100. In TU50, the path near two symbol delays as shown in table C.2, provides beneficial time diversity effect despite the overall channel's dispersive nature. The HT100 has the worst performance due to the fact that only 6-tap estimates result from channel estimation, while HT100 assumes a tap channel.

Both SISO schemes with DDFSE $\mu = 1$ has shown to be effective for soft equalization in EDGE. In general the BCJR MAP variants fare better than the RS-SSA in typical GSM environments but they are more complex than RS-SSA in terms of implementation,
5.3. Reduced Complexity SISOs

Figure 5.5: BER Performance of 8 states SO-DDFSE and RS-SSA over TU50

Figure 5.6: BER Performance of 8 states SO-DDFSE and RS-SSA over HT100
5.3. Reduced Complexity SISOs

Figure 5.7: Subset Trellis Butterfly

subset transitions \((t_k = l \rightarrow t_{k+1} = l')\), the \(n^{th}\) parallel branch transition probability is

\[
\gamma_{k}^{n}(l, l') \propto \frac{1}{2\sigma_{n}^{2}} \left| \tilde{w}_{k} - \tilde{h}_{0} x_{k}(n; t_{k} \rightarrow t_{k+1}) - \sum_{i=1}^{\mu} \tilde{h}_{i} x_{k-i}(t_{k}) - \sum_{i=0}^{L-\mu-1} \tilde{h}_{i+\mu+1} x'_{k-\mu-i-1} \right|^2
\]

(5.37)

where \(x_{k}(n; t_{k} \rightarrow t_{k+1})\) is the symbol \(x_{k}\) associated with the \(n^{th}\) parallel branch transition probability during the subset transition \((t_{k} \rightarrow t_{k+1})\) at epoch \(k\). Similar to DDFSE, the \(x'_{k}\) are the tentative decisions associated to state \(t_{k}\) which are inherited from the previous state having the largest path metric. Denoting the \(N^{2}\) as the set of \(n^{th}\) parallel branch transition probabilities associated to symbol \(x_{k}\) such that the \(i^{th}\) bit of \(x_{k}, b_{k} = l'\) at epoch \(k\), during the subset transition \(t_{k} \rightarrow t_{k+1}\) and vice versa \(N^{0}\) for \(b_{k} = 0'\), the soft output for Log-MAP can be obtained as
5.3. Reduced Complexity SISOs

\[ A(b_{k,i}) = \max_{n \in \mathbb{N}^0, (l,l') \in B_k^1}^\ast (\bar{\alpha}_k(l) + \bar{\gamma}_k^l(l,l') + \bar{\beta}_{k+1}(l')) - \]

\[ \max_{n \in \mathbb{N}^0, (l,l') \in B_k^0}^\ast (\bar{\alpha}_k(l) + \bar{\gamma}_k^l(l,l') + \bar{\beta}_{k+1}(l')) , \]

\[ \bar{\alpha}_k(l) = \max_{l',n}^\ast (\bar{\alpha}_{k-1}(l') + \bar{\gamma}_{k-1}^l(l',l)) , \quad l' = 0, \ldots, Z - 1 \]

\[ n = 1, \ldots, M/J_1 \] \hspace{5cm} (5.39)

\[ \bar{\beta}_k(l) = \max_{l',n}^\ast (\bar{\beta}_{k+1}(l') + \bar{\gamma}_{k}^l(l,l')) , \quad l' = 0, \ldots, Z - 1 \]

\[ n = 1, \ldots, M/J_1 \] \hspace{5cm} (5.40)

The \( M/J_1 \) parallel branches in the forward and backward recursions are summed for each transition as shown in (5.39) and (5.40). The soft output based on Max-Log can be computed by replacing the \( \max^\ast \) by \( \max \) operation in (5.38) to (5.40).

5.3.3.1 Performance of SO-RSSE over Typical GSM channels

Figure 5.8: BLER Performance of SO-RSSE and RS-SSA over RA250

Figure 5.8 to 5.10 illustrates the effects of reducing the complexity of a 8 states SO-DDFSE using the set-partitioning, which results in the 4 and 2 states SO-RSSE. An \( \frac{E_b}{N_0} \) in excess of 14.0 dB at 10% Block Error Rate (BLER) across all channels is required by
5.3. Reduced Complexity SISOs

Figure 5.9: BLER Performance of SO-RSSE and RS-SSA over TU50

Figure 5.10: BLER Performance of SO-RSSE and RS-SSA over HT100
SO-DDFSE, RS-SSA and 4 states SO-RSSE. The 2 states SO-RSSE suffers the most performance degradation which is 2 dB worse than the SO-DDFSE while the 4 states SO-RSSE is less than 1 dB worse at 10% BLER across all channels. This degradation is unavoidable because the hyper-state is a subset of the actual channel state and there are $8/J_1$ parallel branches associated with each subset transition. As in (5.9, 5.10, 5.18 and 5.19), the forward and backward recursions are obtained as the sum over these parallel branches which results in somewhat of an 'average' value. This affects the decisions' reliability on which the LLR in (5.38) are based. However, in SO-DDFSE the branches are still uniquely represented with each subset state transition even though they are truncated to $\mu + 1$ taps thereby offering the best performance. Nevertheless, the 2 state SO-RSSE with MAX-LOG-MAP offers an attractive solution for complexity reduction while RS-SSA seems well suited for EDGE.

Table 5.2 to 5.4 assess the performance of the proposed schemes by benchmarking against the 3GPP EDGE requirements in terms of available implementation margin. Table 5.1 summarizes the required SNR corresponding to the MCS-5 minimum input reference sensitivity for 10% BLER with the following assumptions: a) $8.0\text{dB Noise Figure}$, b) $N_0 = -174\text{dBm/Hz}$ and c) $54\text{ dBHz Noise Bandwidth}$.

<table>
<thead>
<tr>
<th>Reference Sensitivity Benchmark</th>
</tr>
</thead>
<tbody>
<tr>
<td>Propagation Conditions</td>
</tr>
<tr>
<td>Input Sensitivity (dBm)</td>
</tr>
<tr>
<td>Required SNR (dB)</td>
</tr>
</tbody>
</table>

Table 5.1: 3GPP EDGE Requirements Benchmark

The SO-DDFSE with Log-MAP outperforms the rest with a remarkable implementation margin of $8.0\text{dB}$ for RA250 and TU50. Among the various soft output schemes, the 2 state RSSE with BCJR MAP variants have the lowest implementation margin as summarized in table 5.2 to 5.4. Although, their lowest margins are experienced with HT100, but an average margin of about $6.0\text{dB}$ ($5.9\text{dB}$ at least) for all the channel profiles can still be obtained, which can be regarded as comfortable for complexity reduction.
5.3. Reduced Complexity SISOs

<table>
<thead>
<tr>
<th>Scheme</th>
<th>Log-MAP</th>
<th>Max-Log-MAP</th>
<th>SSA</th>
</tr>
</thead>
<tbody>
<tr>
<td>8-DDFSE</td>
<td>8.9</td>
<td>8.5</td>
<td>8.25</td>
</tr>
<tr>
<td>4-RSSE</td>
<td>8.4</td>
<td>8.1</td>
<td>×</td>
</tr>
<tr>
<td>2-RSSE</td>
<td>6.9</td>
<td>7.0</td>
<td>×</td>
</tr>
</tbody>
</table>

Table 5.2: Implementation Margin of Proposed Schemes with RA250, at 10% BLER

<table>
<thead>
<tr>
<th>Scheme</th>
<th>Log-MAP</th>
<th>Max-Log-MAP</th>
<th>SSA</th>
</tr>
</thead>
<tbody>
<tr>
<td>8-DDFSE</td>
<td>8.25</td>
<td>7.9</td>
<td>7.6</td>
</tr>
<tr>
<td>4-RSSE</td>
<td>7.5</td>
<td>7.75</td>
<td>×</td>
</tr>
<tr>
<td>2-RSSE</td>
<td>6.1</td>
<td>6.0</td>
<td>×</td>
</tr>
</tbody>
</table>

Table 5.3: Implementation Margin of Proposed Schemes with TU50, at 10% BLER

<table>
<thead>
<tr>
<th>Scheme</th>
<th>Log-MAP</th>
<th>Max-Log-MAP</th>
<th>SSA</th>
</tr>
</thead>
<tbody>
<tr>
<td>8-DDFSE</td>
<td>7.5</td>
<td>7.4</td>
<td>7.1</td>
</tr>
<tr>
<td>4-RSSE</td>
<td>7.4</td>
<td>7.1</td>
<td>×</td>
</tr>
<tr>
<td>2-RSSE</td>
<td>6.0</td>
<td>5.9</td>
<td>×</td>
</tr>
</tbody>
</table>

Table 5.4: Implementation Margin of Proposed Schemes with HT100, at 10% BLER
5.3.4 Performance of Reduced complexity SISOs under Interference Limited Environment

All the proposed schemes have been shown to be within the requirements of the EDGE standards in terms of sensitivity to thermal noise but they also need to be resistant against interference. Figure 5.11 to 5.15 study the sensitivity of the proposed schemes under the influence of co-channel interference. A single 8-PSK interferer that has independent fading profile from the desired signal is assumed. The perturbation is treated as additive noise which includes both the thermal noise (25.0 dB SNR) and CCI.

First the non frequency hopping scenario is considered as shown in figure 5.11 to 5.13. For all channel profiles the Log-MAP implementation offers negligible improvement to its Max-Log-MAP variants. The RS-SSA performance differs from the SO-DDFSE by not more than 0.25 dB with the 4 state SO-RSSE performing between at 10% BLER. These results suggest that the Log-MAP is sensitive to the statistical nature of the perturbation which is assumed to be Gaussian, while in reality the true noise model is
unknown due to the mixture of both perturbations, where specifically the noise variance is a parameter input for the Log-MAP.

The performance degradation of 2 state RSSE clearly shown in figure 5.11, which is approximately 1.0 dB worse than the rest of the soft output schemes at 10% BLER. The worst is experienced with TU3 (12%BLER at 20dB SIR) while only 0.2 dB worse is observed for RA250. Even with higher numbers of trellis states like the SO-DDFSE, it requires a SIR in excess of 19.5 dB which is 3 dB higher than what is required in TU50 at 10% BLER. This is because TU3 represents pedestrian speeds and experience longer time sitting in deep fades and so the interleaving depth is not sufficiently long to randomize the error burst before decoding, while in TU50 and RA250, the mobile passes through fades quickly. The RA250 has the best performance, requiring a SIR of 15.5 dB, that is about 0.7 dB better than TU50 at 10% BLER. However, severe Doppler effect contributes to channel degradation, which in turn causes high fading rates that make channel estimation inaccurate, and finally results in the irreducible error floor at high SIR as shown in figure 5.13.
5.3. Reduced Complexity SISOs

Figure 5.13: BLER Performance of SO-RSSE and RS-SSA over RA250 without FH with CCI

Figure 5.14 to 5.15 demonstrates the beneficial effects of ideal frequency hopping on the various reduced complexity soft output schemes. As before, Log-MAP offers marginal improvement over the Max-Log-MAP and SSA. The greatest improvement with frequency hopping is found in the TU3 channel. The improvement in gain over the non frequency hopping case in figure is tabulated as follows in table 5.5.

<table>
<thead>
<tr>
<th>TU3, Frequency Hopping Gain</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scheme</td>
</tr>
<tr>
<td>SO-DDFSE</td>
</tr>
<tr>
<td>RS-SSA</td>
</tr>
<tr>
<td>4-RSSE</td>
</tr>
</tbody>
</table>

Table 5.5: TU3 Improvement Gain with Ideal Frequency Hopping, at 10% BLER

The benefit of frequency hopping is at least 2.4 dB as seen in table 5.5. For 2 state SO-RSSE, it requires a SIR in excess 18.5 dB at 10% BLER where previously the BLER is 12% with 20 dB SIR. This implies that at least 1.5dB gain is achievable at 10%
5.3. Reduced Complexity SISOs

BLER. However, the improvement is much smaller for TU50. Comparing to the case without frequency hopping in figure 5.11, the gain is about 1.0 dB and 0.8 dB for SO-DDFSE and RS-SSA respectively at 10% BLER while the 4 state SO-RSSE performs between. Therefore, frequency hopping is beneficial to slow moving mobiles such as in the case of TU3. With ideal frequency hopping, each transmitted burst is subjected to independent fading which reduces the chance of a slow moving mobile sitting in a deep fade. The SO-DDFSE with Log-MAP has been shown to outperform the various

![Figure 5.14: BLER Performance of SO-RSSE and RS-SSA over TU50 with FH with CCI](image-url)

reduced state soft output schemes in an interference limited environment. However, the improvement offered is marginal compared to RS-SSA and 4 state SO-RSSE due to the factors summarized as follows:

i) 'White' Gaussian assumption of interference noise;

ii) decision feedbacks errors

iii) noise variance estimation errors for Log-MAP.

For factor i) and ii), both errors enhance residual ISI, CCI and noise, thereby reducing
5.4 Cascaded Soft-output RSSE

The 2 state SO-RSSE with Log-MAP is still preferred for complexity reduction despite its degraded performance caused by the various factors discussed previously. The noise variance estimation incurred complexity but it can be considered as an additional degree
of freedom to improve the overall performance. To overcome the drawbacks of the 2 state SO-RSSE, a new improved scheme involving the 2 state RSSE and a Log-MAP estimator in cascade, is proposed to reduce the decision feedback errors and inaccurate noise variance estimation. As shown in figure 5.16 the 2 state RSSE produces

![Figure 5.16: Cascaded SO-RSSE](image)

a noise variance estimate, $\sigma_n^2$, associated with the final hard-decision outputs, $\hat{x}_1^K = \{\hat{x}_1, \ldots, \hat{x}_{K-1}, \hat{x}_K\}$ which will be used by the Log-MAP estimator in the following stage. The signal at the input of the Log-MAP estimator is

$$\bar{y}_k = \tilde{v}_k - \sum_{i=\mu+1}^{L} \tilde{h}_i \hat{x}_{k-i}$$

$$= \sum_{i=0}^{\mu} \tilde{h}_i x_{k-i} + \sum_{i=\mu+1}^{L} \tilde{h}_i (x_{k-i} - \hat{x}_{k-i}) + n_k$$

$$= \sum_{i=0}^{\mu} \tilde{h}_i x_{k-i} + n'_k$$

(5.41)

where

$$n'_k = \sum_{i=\mu+1}^{L} \tilde{h}_i (x_{k-i} - \hat{x}_{k-1}) + n_k$$

(5.42)

are the noise samples that include the decision feedback errors and the additive noise at the pre-filter output respectively. The variance of $n'_k$ can be estimated by averaging
over the received sequence period i.e. centre to end or start of time slot, depending on the direction of equalization.

\[
\sigma_{n'}^2 \Delta \mathbb{E}[|n'_k|^2] \\
\approx \frac{1}{K} \sum_{k=1}^{K} |n'_k|^2 \\
= \frac{1}{K} \sum_{k=1}^{K} \left( \sum_{i=\mu+1}^{L} \tilde{h}_i(x_{k-i} - \hat{x}_{k-i}) + n_k \right)^2 
\]

(5.43)

Other workers \cite{19, 21} estimate the noise variance using the TS at the centre of the burst, the current approach estimate the noise variance from the final hard decisions of the first stage RSSE. At the end of the sequence estimation, the hard decisions, is obtained by selecting the path corresponding to the minimum path metric which is equivalent to the sum of the branch metrics associated with the hard decisions \( \hat{x}_{1}^{K} \) as shown

\[
\hat{x} = \min_{K} \left( \min_{i_{K-1}} (\min_{i_{K-2}} (\cdots (\min_{i_1} (\chi(t_1) + e(t_1 \rightarrow t_2)) \cdots) + e_{K-1}(t_{K-1} \rightarrow t_k)) \right) \\
= \sum_{k=1}^{K} |\hat{v}_k - \sum_{i=0}^{L} \tilde{h}_i \hat{x}_{k-i}|^2 
\]

(5.44)

By averaging the accumulated error metric in (5.44) over the sequence length, \( K \), the noise variance, \( \sigma_{n'}^2 \), is obtained

\[
\sigma_{n'}^2 = \frac{1}{K} \sum_{k=1}^{K} \left| \hat{v}_k - \sum_{i=0}^{L} \tilde{h}_i \hat{x}_{k-i} \right|^2 
\]

(5.45)

Using the ISI model of figure 5.1, (5.45) can be expressed as

\[
\sigma_{n'}^2 = \frac{1}{K} \sum_{k=1}^{K} \left| \sum_{i=0}^{L} \tilde{h}_i x_{k-i} + n_k - \sum_{i=0}^{L} \tilde{h}_i \hat{x}_{k-i} \right|^2 \\
= \frac{1}{K} \sum_{k=1}^{K} \left| \sum_{i=0}^{\mu} \tilde{h}_i (x_{k-i} - \hat{x}_{k-i}) + \sum_{i=\mu+1}^{L} \tilde{h}_i (x_{k-i} - \hat{x}_{k-i}) + n_k \right|^2 \\
= \frac{1}{K} \sum_{k=1}^{K} \left| \sum_{i=0}^{\mu} \tilde{h}_i (x_{k-i} - \hat{x}_{k-i}) + \hat{x}_{k-i} + n_k \right|^2 
\approx \sigma_{n'}^2 
\]

(5.46)

as in (5.43) Compared to the previous estimation method using the LS in (3.17), \( \sigma_{n'}^2 \) is averaged over more samples including the data period, which results in a less biased estimate.
The Log-MAP in CSO-RSSE can be considered as a soft output DDFSE or RSSE where it uses the final hard decisions from the previous stage RSSE as decision feedback to truncate the length of TOCIR as shown in the figure (5.41). Therefore the branch transition probability is now based on $\hat{h}_0^m$ and the estimated noise variance, $\sigma^2_n$, and can be generalized for the RSSE as

$$p_i^m(l, l') \propto -\frac{1}{2\sigma^2_n} \left| \hat{y}_k - \hat{h}_0 x_k(n; t_k \rightarrow t_{k+1}) - \sum_{i=1}^{\mu} \hat{h}_i x_{k-i}(t_k) \right|^2$$ (5.47)

where $x_k(n; t_k \rightarrow t_{k+1})$ is the symbol $x_k$ associated to the $n^{th}$ parallel branch transition probability during the subset transition ($t_k \rightarrow t_{k+1}$) at epoch $k$.

### 5.4.1 Performance of CSO-RSSE over Interference Limited Environment

Figure 5.17 and 5.18 consider the case of a non frequency hopping environment under the influence of a co-channel interferer. Two configurations of the CSO-RSSE are studied. Both employ a 2 state RSSE but in cascade with either a 8 state or a 2 state Log-MAP estimator. For the TU50 channel, the CSO-RSSE with 8 state Log-MAP
5.4. Cascaded Soft-output RSSE

Figure 5.18: BLER Performance of CSO-RSSE over TU3 without FH with CCI

offers a benefit of about 0.8 dB and 1.0 dB gain over the SO-DDFSE and RS-SSA respectively at 10% BLER, while the cascaded scheme with 2 state Log-MAP provides a significant gain of 1.2 dB over the 2 state SO-RSSE. For the TU3 channel similar improvement is also observed. The 8 state Log-MAP CSO-RSSE requires a SIR in excess of 18.9 dB which is about 0.7 dB and 1.1 dB better than the SO-DDFSE and RS-SSA at 10% BLER. With the cascaded scheme, 10% BLER is achievable at 20 dB SIR, which is not possible for 2 state SO-RSSE.

These results suggest that the final hard decisions are more reliable than the tentative decisions. The SO-DDFSE, SO-RSSE and RS-SSA employ decision feedback based on tentative decisions in the removal of residual ISI, $\tilde{h}_{\mu+1}$, while the cascaded scheme uses the hard decisions which reduces the feedback errors. Moreover, the noise variance obtained from the final hard decisions are less biased due to longer averaging and therefore improves the Log-MAP's accuracy in estimating the soft outputs.

Figure 5.19 and 5.20 illustrate the effects of ideal frequency hopping on the cascaded scheme. For TU50 with frequency hopping, the benefit for 8 and 2 state CSO-RSSE is an improvement of 0.8 dB over the non frequency hopping case. The cascaded scheme
5.5 Summary and Conclusions

is 0.7 dB and 1.0 dB better than the SO-DDFSE and RS-SSA respectively, while the 2 state CSO-RSSE is only 0.6 dB worse than the 8 state at 10% BLER. This makes the 2 state cascaded scheme approximately 0.2 dB better than the SO-DDFSE and offering an advantage of 1 dB gain over the 2 state SO-RSSE.

Considering the cascaded schemes with ideal frequency hopping in TU3, there is about 2.0 dB advantage over the non frequency hopping at 10% BLER, but the 8 state CSO-RSSE is only 0.2 dB and 0.6 dB better than SO-RSSE and RS-SSA. Similarly, the 2 state SO-RSSE is about 0.3 dB worse than the cascaded scheme at 10% BLER.

Figure 5.19: BLER Performance of CSO-RSSE over TU50 with FH with CCI

5.5 Summary and Conclusions

This chapter has investigated low complexity soft output trellis equalizers that are practical for implementation in EDGE. First, the concept of DDFSE is introduced to the SSA and the BCJR MAP in the logarithmic domain, where the 8 state SO-DDFSE and RS-SSA are developed and they are shown to be capable of equalization for EDGE over the GSM channel profiles.
Although the SO-DDFSE is shown to perform well in GSM channels, it requires higher complexity than the RS-SSA, even though both have the same number of trellis states. For further complexity reduction, the set partitioning technique is applied to SO-DDFSE and with the use of decision feedback, the required trellis states are reduced to a 4 and 2 state SO-RSSE. The effects of reduced complexity are addressed and the results suggest that all these schemes are able to perform with comfortable implementation margins over the GSM channel profiles.

Among them the 2 state soft output RSSE suffered the most degradation due to inaccurate soft decisions caused by the effects of set partitioning resulting in the averaging of parallel branches. In addition, like the SO-DDFSE, it is also degraded by decisions feedback errors and mismatched noise statistics. Subsequently, an improved two stage approach that segregates the reduced state trellis equalizer and the MAP estimator into two cascaded stages was implemented. The cascaded scheme makes use of final hard decisions from the 2 state RSSE as feedback decisions while in SO-DDFSE and SO-RSSE the tentative decisions are employed. The noise variance is also estimated from the hard decisions which uses a longer average over the data symbols and thus
results in a more unbiased and accurate estimate. The cascaded schemes are studied along with the single stage soft output schemes over an interference limited environment with ideal frequency hopping and without. The results shows that frequency hopping is highly desirable for slow-moving mobiles as in the TU3 channel, where at least 2 dB benefit is observed for both the single stage and cascaded schemes. However, it has a smaller effect (limited to 1 dB gain) on moderate speed mobiles like TU50. The results also confirm that the two stage method is a better approach than the single stage soft output. However, with improved noise variance estimation and reduced decision feedback errors, the cascaded method cannot avoid the degradation due to trellis reduction especially for a 2 state Log-MAP. Nevertheless, the cascaded 2 state Log-MAP is still an improved method over the 2 state SO-RSSE for complexity reduction.
Chapter 6

Joint Channel, Pre-filter and Soft Output Data Estimation for EDGE

6.1 Introduction

In this chapter a new joint pre-filter, channel and data estimation scheme that involves the DDFSE is proposed to mitigate the effects of fast-time varying channels. The PSP approach is adopted for tracking the channel derived parameters that includes the pre-filter and the transformed OCIR. In order to minimize the computation effort the LMS adaptation algorithm is employed as the tracking mechanism. For further reduction in complexity, the joint scheme is extended to RSSE where set-partitioning is involved. Subsequently, the BCJR MAP variants and SSA are applied and results in adaptive soft output algorithms of various complexity. In particular for Log-MAP which requires good statistical knowledge of the perturbation and is often penalized by its sensitivity to mismatch, an improved scheme that employs the joint scheme and Log-MAP in cascade is proposed. Both schemes are investigated over fast time varying interference limited channels and finally their performance is also evaluated over a very fast channel that represents the situation of a high speed train.
6.2 Joint Channel, Pre-filter and Data Estimation

As discussed in chapter 2, various joint channel and data estimation schemes that involve the PSP and MLSE has been proposed for channels with extreme dynamics [24-26]. However, these methods are too complex for implementation in EDGE due to the number of trellis states required by the MLSE. Trellis reduction is therefore necessary but comes with a disadvantage, as reduced states algorithms are sensitive to the channel phase. They require a pre-filter prior to the equalizer to pre-process the channel such that the OCIR seen by the equalizer is of minimum phase nature. The pre-filter and the TOCIR are channel derived parameters, where the channel itself is time varying and unknown a priori in a mobile communication environment. This implies that parameter tracking is essential especially when the frequency selective fading channel is varying dynamically, such as the scenario of a high speed train.

6.2.1 Parameters Adaptation with LMS Algorithm

Consider the channel model of memory $L$,

$$\bar{v}_k = \bar{h}_k^T \bar{x}_k + n_k \quad (6.1)$$

and $\bar{v}_k$ is the signal at the output of the pre-filter

$$\bar{v}_k = r_k^T \bar{h}_k \quad (6.2)$$

where $\bar{x}_k = \{x_{k-1}, \ldots, x_{k-L}\}^T$ is the $L$-element vector of the transmitted symbols. The pre-filter, $\bar{u}_k = \{\bar{u}_{0:k}, \ldots, \bar{u}_{P+L,k}\}^T$ and the TOCIR, $\bar{h}_k = \{\bar{h}_{0:k}, \ldots, \bar{h}_{L:k}\}^T$ are the two sets of channel derived time varying parameters where the data estimation depends on a priori information. The idea is to estimate these parameters jointly with the data. The PSP method is adopted as it is inherently deployed in reduced trellis techniques like the DDFSE and RSSE, to cancel the effects of residual ISI due to the approximation of a full trellis by a smaller set. However, even with a pruned trellis, each state is associated with a set of parameters to be updated. In order to maintain low computation effort during tracking, the LMS algorithm is employed.
According to the method of Steepest Descent (SD), the value of tap weight $w_{k+1}$ at time $k+1$ can be updated as follows [20]

$$w_{k+1} = w_k + \frac{1}{2} \epsilon (-\frac{\partial J}{\partial w_k})$$

(6.3)

where $\epsilon$ is a positive value constant and $J$ is the cost function, which is defined as the Mean Square Error (MSE)

$$J \triangleq E[|e_k|^2] \triangleq E[e_k e_k^*]$$

(6.4)

$$= E[|\hat{u}_k - \tilde{h}_k^T x_k|^2]$$

(6.5)

$$= E[|r_k^T u_k - \tilde{h}_k^T x_k|^2]$$

(6.6)

Using the method of SD, the partial derivatives of the cost function, MSE in (6.5) and (6.6) are first obtained as

$$\frac{\partial J}{\partial \hat{h}_k} = -2E[x_k^* e_k]$$

(6.7)

$$\frac{\partial J}{\partial \tilde{u}_k} = 2E[r_k^* e_k]$$

(6.8)

Subsequently, the parameters are updated accordingly as

$$\hat{h}_{k+1} = \hat{h}_k + \frac{1}{2} \epsilon (2E[x_k^*])$$

(6.9)

$$\tilde{u}_{k+1} = \tilde{u}_k + \frac{1}{2} \kappa (-2E[r_k^* e_k])$$

(6.10)

The parameters update is then approximated using the LMS adaptation [20] by ignoring the expectation operator in (6.7) and therefore, the TOCIR and pre-filter coefficients can be tracked using LMS as follows

$$\hat{h}_{k+1} = \hat{h}_k + \epsilon (x_k^* e_k)$$

(6.11)

$$\tilde{u}_{k+1} = \tilde{u}_k - \kappa (r_k^* e_k)$$

(6.12)

where $\epsilon$ and $\kappa$ are the adaptation factors chosen as a compromise between excessive MSE and tracking capability.

6.2.2 Parameters Tracking with LMS using PSP

After obtaining the LMS update of the parameters, they can then be incorporated into the reduced state data estimation structure as shown in figure 6.1. Consider
6.2. Joint Channel, Pre-filter and Data Estimation

Figure 6.1: Joint Channel, Pre-filter and Data Estimation

the channel of memory $L$ being equalized by the RSSE with trellis size truncated to $Z = M^\mu$. Following the notations in chapter 4, the unknown, time varying TO-CIR, $\{\tilde{h}_{i,k}\}_{i=0}^{Z-1}$ and the pre-filter, $\{\tilde{u}_{i,k}\}_{i=0}^{Z-1}$ can be represented by the parameter vectors as $\tilde{h}(t_k^\mu) = \{h_0(t_k^\mu), \ldots, h_L(t_k^\mu)\}^T$ and $\tilde{u}(t_k^\mu) = \{u_0(t_k^\mu), \ldots, u_{F+L}(t_k^\mu)\}^T$ respectively. The vector $\tilde{h}(t_k^\mu)$ consists of two parts, $\tilde{h}^\mu(t_k^\mu) = \{\tilde{h}_0(t_k^\mu), \ldots, \tilde{h}_{\mu+L}(t_k^\mu)\}^T$ and $\tilde{h}^{\mu+1}(t_k^\mu) = \{\tilde{h}_{\mu+1}(t_k^\mu), \ldots, \tilde{h}_L(t_k^\mu)\}^T$ to be processed by the MLSE and the decision feedback respectively.

For each successor subset state $t_{k+1}^\mu$, the survivor path metric, $\chi(t_{k+1}^\mu)$ is computed as:

$$\chi(t_{k+1}^\mu) = \min_{t_k^\mu} \left( \chi(t_k^\mu) + \left| e(t_k^\mu \rightarrow t_{k+1}^\mu) \right|^2 \right)$$

and the branch metric, $e(t_k^\mu \rightarrow t_{k+1}^\mu)$ at epoch $k$ is

$$\left| e(t_k^\mu \rightarrow t_{k+1}^\mu) \right|^2 = \left| \bar{o}(t_k^\mu) - \tilde{h}^\mu(t_k^\mu)^T x(t_k^\mu \rightarrow t_{k+1}^\mu) - \tilde{h}^{\mu+1}(t_k^\mu)^T x'(t_k^\mu) \right|^2$$

where the received signal vector $r_k = \{r_k, r_{k-1}, \ldots, r_{k-P-L}\}^T$, $x(t_k^\mu \rightarrow t_{k+1}^\mu)$ is the transmitted symbol vector associated to the transition $(t_k^\mu \rightarrow t_{k+1}^\mu)$ at epoch $k$, $x'(t_k^\mu) = \{x_{k-\mu-1}, \ldots, x_{k-L}\}^T$ is the tentative decision vector on past transmitted symbols corresponding to the decision feedback taps.
6.2. Joint Channel, Pre-filter and Data Estimation

Using the LMS algorithm derived for the TOCIR and pre-filter in (6.11) and (6.12), the parameter estimates are updated based on the survivors obtained by applying the minimum survivor metric as in (6.13), over the transitions \( t_k^\mu \rightarrow t_{k+1}^\mu \) as follows

\[
\hat{h}(t_{k+1}^\mu) = \hat{h}(t_k^\mu) + \epsilon \sigma(t_k^\mu \rightarrow t_{k+1}^\mu) x^*(t_k^\mu \rightarrow t_{k+1}^\mu)
\]

(6.15)

\[
\hat{u}(t_{k+1}^\mu) = \hat{u}(t_k^\mu) - \kappa \sigma(t_k^\mu \rightarrow t_{k+1}^\mu) R_k^x
\]

(6.16)

The constants \( \epsilon \) and \( \kappa \) are selected as a compromise between tracking capability and excess MSE. The values are determined experimentally and its best tracking performance are discussed in section 6.2.3. Initially the parameters and the start state of the RSSE are unknown. They are found by the correlation method as described in section 3.6, where the timing synchronization is first obtained. The joint scheme then proceeds bi-directionally starting from the centre to the start and end of the time slot. The operation is carried on a per time slot basis.

6.2.3 Performance of PSP-LMS over Fast Time-varying Frequency Selective Fading Channels

The effects of reduced trellis on parameter tracking under the fast time-varying frequency selective fading channel are investigated in figure 6.2 to 6.4. The RA channel of the various speeds (100km/h, 250km/h and 300km/h) are considered for simulating the fast time varying channel while the RA300 represents the scenario of a high speed train. The first ray in the RA profile is Rayleigh instead of Ricean in order to create a more hostile environment and additionally, uncoded transmission is assumed so as to demonstrate the capability of the proposed joint scheme.

Without adaptation, an irreducible error floor of 3.5% and 5% BER are observed for RA250 and RA300 respectively at high \( \frac{E_b}{N_0} \). The error floor arises due to the effects of high Doppler spread. Without adaptation, the channel parameters derived at the centre of the burst are used for equalization throughout the burst even though the channel varies significantly towards the start and the end of the burst. As a result, the channel parameters, especially the pre-filter become somewhat an 'average' as they are not adapted over the time varying channel. This causes inaccurate channel estimates,
6.2. Joint Channel, Pre-filter and Data Estimation

Figure 6.2: BER Performance of 8 states DDFSE over RA channel with PSP-LMS tracking

Figure 6.3: BER Performance of 4 states DDFSE over RA channel with PSP-LMS tracking
which the trellis equalizer depended on for data estimation. With adaptation, the error floor in RA250 and RA300 is effectively reduced to 1.5% and 1.9% BER respectively with an adaptation factor of 0.1. In RA100 the channel does not vary quite as much as RA250 and RA300, and hence a smaller adaptation factor of 0.0625 is sufficient. An improvement of about 4.0dB over no adaptation is observed at 1% BER. The result suggests in all speed cases, the joint scheme is effective in reducing the error floor significantly, especially in the case of a high speed train (RA300).

There is no noticeable difference in performance between the various states RSSE over the RA channel, with and without adaptation. Firstly, the result confirms the pre-filtering method is capable of creating a minimum phase channel suitable for RSSE. Secondly, the LMS adaptation with PSP is effective in tracking the parameters such that the minimum phase characteristics required by the RSSE are maintained as suggested in figure 6.4 where the 2 state RSSE performance is highly similar to the 8 state DDFSE in figure 6.2.

Figure 6.5 shows the performance of 8, 4 and 2 state adaptive RSSE over the various
6.2. Joint Channel, Pre-filter and Data Estimation

Figure 6.5: BER Performance with adaptation

GSM profiles. For the TU100 channel, an improvement of 1 dB at $10^{-2}$ BER over no adaptation is achieved with an adaptation factor of 0.0625, which is slightly better than the TU50 (without adaptation). This is because in TU50 the coherence time of the channel is much larger than the burst duration, therefore the channel characteristics near the start and end of the burst do not vary significantly and reasonable performance can still be achieved by just bi-directional equalization using the channel estimates derived at the centre of the burst. No significant degradation is observed between the various trellis state configurations, which suggest that the pre-filtering method is capable of providing the appropriate phases prior to equalization even with a highly dispersive channel like TU. The results also confirms the parameter tracking method in upholding the required channel phase characteristics over a fast time varying highly dispersive fading channel like the TU100.

A significant error floor of 3% BER is observed at high $\frac{E_b}{N_0}$ due to the fact that only 6-tap estimates result from the channel estimation, while 8 tap OCIR is assumed. No improvement is observed with LMS tracking. This suggest that the parameter tracking copes with fast variations in the channel, but not the inaccuracy in the channel
6.3 Adaptive Soft Decisions Data Estimation

Using the LMS update with PSP, the joint channel, pre-filter and data estimation scheme has proved to be effective in mitigating the undesirable effects of severe Doppler spreading. The next task is to extend the joint scheme so as to incorporate the symbol-by-symbol decisions with the interest in reduced complexity.

6.3.1 Adaptive RS-SSA

The previous soft output algorithms in chapter 5 assume channel state information derived at the centre of the time slot is quasi-stationary throughout the burst. However, when the channel taps are modelled as unknown and time varying parameters, the corresponding soft output in (5.20) would have to be modified to include \( \hat{h}_k \), which the SSA requires to compute the soft output as shown

\[
Pr(x_{k-\delta}; \tilde{\sigma}_1^1 | \hat{h}_k) = \sum_{s_{k+1}} Pr(x_{k-\delta} | s_{k+1}; \tilde{\sigma}_1^1, \hat{h}_k) Pr(s_{k+1} | \tilde{\sigma}_1^1 | \hat{h}_k) \tag{6.17}
\]

As the pre-filter and the TOCIR are estimated jointly with data, the branch transition probability in (5.22) at epoch \( k \), during the transition \( t^\mu_k \rightarrow t^\mu_{k+1} \) now requires and depends on the knowledge of parameters that are jointly estimated in epoch \( k - 1 \). Therefore the branch transition probability is

\[
\tilde{\gamma}_k(s_k | \hat{h}(t^\mu_k); \tilde{u}(t^\mu_k)) = -C_1 \ln Pr(s_{k+1} = l'; \tilde{v}_k | s_k = l; \hat{h}(t^\mu_k); \tilde{u}(t^\mu_k)) + C_2 \tag{6.18}
\]

\[
= \left| \begin{bmatrix} \tilde{u}(t^\mu_k) - \tilde{\mu}(t^\mu_k)^T x(t^\mu_k \rightarrow t^\mu_{k+1}) - \tilde{h}_k(t^\mu_k)^T x'(t^\mu_k) \end{bmatrix} \right|^2 \tag{6.19}
\]

which is identical to the branch metric obtained in (6.14). Here, the same scaling constants in (5.23), \( C_2 = C_1 \ln \left( \frac{1}{2\pi \sigma_n^2} Pr(s_{k+1} | s_k) \right) \) and \( C_1 = 2\sigma_n^2 \) are applied while \( Pr(s_{k+1} | s_k) \) is assumed constant.

The soft decision computation becomes straightforward by first associating the branch metric with branch transition probability, which is directly applied to the procedure
6.3. Adaptive Soft Decisions Data Estimation

from (5.29) to (5.32). Subsequently, the parameters are updated in (6.11) and (6.12) using the same branch metric and thus the symbol-by-symbol decision is obtained jointly with the channel and pre-filter for the transition \( t_k^l \to t_{k+1}^l \) at epoch \( k \).

6.3.2 Adaptive SO-RSSE/DDFSE

In chapter 5, the SO-RSSE of various complexity configurations employs the BCJR MAP algorithm in the logarithmic domain, and is being demonstrated for soft output equalization over interference limited and quasi-stationary channels. However, its application in the context of joint parameters and soft output detection is not as straightforward as in the case of SSA. This is due to the backward recursion in the BCJR algorithm.

Consider the forward recursion in SO-RSSE. The branch transition probability can be adapted in the same manner as in adaptive RS-SSA. At epoch \( k \), during the subset transition \( (t_k = l \to t_{k+1} = l') \), the \( n^{th} \) parallel branch transition probability is

\[
\gamma^l_k(l', l|\tilde{h}(t_k^l), \tilde{h}(t_{k+1}^{l'})) \propto \frac{1}{2\sigma_n^2} \left| r_k^T \tilde{u}(t_k^l) - \tilde{h}_k^{l}(t_k^l)^T x(n; t_k^l \to t_{k+1}^{l'}) - \tilde{h}_{k+1}^{l+1}(t_k^l)^T x'(t_{k+1}^{l'}) \right|^2
\]

(6.20)

where \( x(n; t_k^l \to t_{k+1}^{l'}) \) represents the symbol vector associated to the \( n^{th} \) parallel branch transition probability during the subset transition \( (t_k \to t_{k+1}) \) at epoch \( k \).

For the backward recursion, it is done in the non-adaptive manner using the transition metrics and parameters obtained in the forward adaptive step. Strictly speaking, the backward pass can have its own trellis and results in a different state definition from the forward pass. This is avoided by applying the forward pass trellis to the backward pass which is the adopted method for SO-RSSE and SO-DDFSE. By doing so the backward pass assumes the values for decision feedback in the forward pass as shown in figure 6.6. The unshaded and shaded boxes represent the state handled by MLSE and decisions feedback respectively. During the transition time \( k \to k+1 \) in the forward recursion, the decisions fed back are the least recent symbols and are updated from the best survivor path. In the backward pass during the transition time \( k+1 \to k \), instead of updating the decision feedback symbols at each stage, the decisions feedback symbols from the
forward recursion are assumed so that the same state definition and branch transition probability can be used as before. Similarly, this idea is applied to the parameters adaptation of the backward pass whereby the forward updated transition metrics are used by the backward pass and therefore it only requires half the actual computation effort in parameter tracking. In addition it does not need additional storage of the transition metrics and parameters as they are already obtained and stored during the forward processing; the whole burst would have to buffered anyway due to the fact that the equalization proceeds bi-directionally from the centre of the burst.

6.3.3 Performance of Adaptive Soft-Decision Data Estimation over Fast Time-varying Frequency Selective Fading, Interference Limited Channel

The performance of the various reduced state joint parameters and soft output estimation developed in section 6.3.1 and 6.3.2 are determined over a fast time-varying frequency selective fading channel as shown in figure 6.7 to 6.9. In order to have a realistic evaluation, the channel is corrupted by a co-channel interferer in addition to thermal noise.

There is no significant difference between various logarithmic MAP implementations as
seen in figure 6.7 for both with and without adaptation in RA250 and RA300 channels. The main reason is due to Log-MAP's sensitivity to the noise variance estimate. In addition to thermal noise and interference, the noise now includes the tracking errors caused by imperfect adaptation. Therefore, it performs only as well as the sub-optimal RS-SSA, which is less complex than SO-DDSE although both have identical trellis size. This implies the RS-SSA is a more favourable choice than Max-Log-MAP as it requires only forward recursion.

An excess of 16.6 dB and 17.5 dB SIR is required by the SO-DDFSE with and without adaptation respectively over the RA300 channel at 10% BLER. This is 1.5 dB and 0.8 dB higher than what is required in the RA250, with and without adaptation. Hence with adaptation, the RA300 is only 0.8 dB worse than RA250. Similar performance is also observed for 4 state ASO-RSSE. For complexity reduction, the 2 state SO-RSSE would require a SIR in excess of 17 dB and 18 dB with and without adaptation over the RA300 at 10% BLER. This is about 0.5 dB worse than the 8 state ASO-DDFSE for RA300 channel and similar degradation of 0.5 dB and 0.2 dB is experienced for RA250 with and without adaptation respectively. The results suggest that with a reduced complexity of 2 states, an additional 0.5 dB SIR, it is possible to support mobiles of high vehicular speeds as in RA300, although not required by the EDGE standards.

6.4 Adaptive Two Stage Soft Decision Data Estimation

Figure 6.10 shows the structure of Adaptive CSO-RSSE that consists of a joint parameter and data estimator in cascade with a reduced state Log-MAP soft output estimator. Similar to the operation of CSO-RSSE in chapter 5, it employs the final hard decisions, \( \hat{x}_k \), from the joint estimator in the first stage as decision feedback to truncate the TOCIR and meanwhile utilize its corresponding path metric to estimate the noise variance as shown in (5.45). Besides the noise variance, the Log-MAP requires the knowledge of the time-varying TOCIR which is now tracked in the previous stage. By back tracing the path in trellis, that leads to the final hard decisions, the parameters can be obtained the first stage as \( \tilde{h}(t^*_k|\hat{x}_k) = \{ \tilde{h}_0(t^*_k|\hat{x}_k), \ldots, \tilde{h}_L(t^*_k|\hat{x}_k) \}^T \) and \( \tilde{u}(t^*_k|\hat{x}_k) = \{ \tilde{u}_0(t^*_k|\hat{x}_k), \ldots, \tilde{u}_L(t^*_k|\hat{x}_k) \}^T \). The reduced state Log-MAP requires the
Figure 6.7: BLER Performance of 8 states ASO-DDFSE over RA channel

Figure 6.8: BLER Performance of 4 states ASO-RSSE over RA channel
6.4. Adaptive Two Stage Soft Decision Data Estimation

Figure 6.9: BLER Performance of 2 states ASO-RSSE over RA channel

Figure 6.10: Adaptive Cascaded SO-RSSE
first \( \mu + 1 \) taps, \( \tilde{h}_\mu(t_k^\mu|\tilde{x}_k) = \{\tilde{h}_0(t_k^\mu|\tilde{x}_k), \ldots, \tilde{h}_L(t_k^\mu|\tilde{x}_k)\}^T \), while the decision feedback process uses the last \( L - \mu \) taps, \( \tilde{h}_{\mu+1}(t_k^\mu|\tilde{x}_k) = \{\tilde{h}_{\mu+1}(t_k^\mu|\tilde{x}_k), \ldots, \tilde{h}_L(t_k^\mu|\tilde{x}_k)\}^T \). With these parameters, the input signal \( \tilde{y}_k \) to the Log-MAP can then be expressed as
\[
\tilde{y}_k = r_k^T \tilde{u}(t_k^\mu|\tilde{x}_k) - \tilde{h}_{\mu+1}(t_k^\mu|\tilde{x}_k)^T \tilde{x}_{\mu+1}
\] (6.21)
where \( \tilde{x} = \{\tilde{x}_{k-\mu-1}, \ldots, \tilde{x}_{k-L}\}^T \). Hence the \( n^{th} \) parallel branch transition probability is
\[
\hat{\gamma}_k(n, l') \propto \frac{1}{2\sigma_n^2} \left| \tilde{y}_k - \tilde{h}_\mu(t_k^\mu|\tilde{x}_k)^T \bar{x}(n; t_k^\mu \rightarrow t_{k+1}^\mu) \right|^2
\] (6.22)
where \( \bar{x}(n; t_k^\mu \rightarrow t_{k+1}^\mu) \) is the transmitted symbol vector associated to \( n^{th} \) parallel transition during the subset transition \( t_k^\mu \rightarrow t_{k+1}^\mu \) at epoch \( k \).

6.4.1 Noise Variance Sensitivity in Fast Time-varying Channel

For the noise variance estimation, the input signal to the Log-MAP can be expanded as follow
\[
\tilde{y}_k = \sum_{i=0}^{P+L} \bar{u}_i(t_k^\mu|\tilde{x}_k)r_{k-i} - \sum_{i=\mu+1}^{L} \tilde{h}_i(t_k^\mu|\tilde{x}_k)\tilde{x}_{k-i}
\] (6.23)
Due to imperfect tracking, the parameters associated with the final hard output can be expressed as
\[
\bar{u}_i(t_k^\mu|\tilde{x}_k) = \bar{u}_{i;k} + \theta_{i;k}
\] (6.24)
\[
\tilde{h}_i(t_k^\mu|\tilde{x}_k) = \tilde{h}_{i;k} + \phi_{i;k}
\] (6.25)
where \( \theta_{i;k} \) and \( \phi_{i;k} \) represent the deviation between the actual time varying parameters and the best estimate obtained from the final hard output in the first stage. The input signal to the Log-MAP is expressed as
\[
\tilde{y}_k = \sum_{i=0}^\mu \tilde{h}_{i;k} \tilde{x}_{k-i} + \eta_k
\] (6.26)
where
\[
\eta_k = \sum_{i=\mu+1}^{L} \tilde{h}_{i;k}(x_{k-i} - \hat{x}_{k-i}) + \left( \sum_{i=0}^{P+L} \theta_{i;k} r_{k-i} - \sum_{i=\mu+1}^{L} \phi_{i;k} \tilde{x}_{k-i} \right) + \eta_k
\] (6.27)
6.4. Adaptive Two Stage Soft Decision Data Estimation

is the noise including the additive noise at the pre-filter output, decision errors and tracking errors. The expression also represents the extreme case of non-adaptation, while with ideal tracking it results in (5.43). Using the same derivations in (5.43), the noise variance of ACSO-RSSE is

$$\sigma^2_n = \frac{1}{K} \sum_{k=1}^{K} \left| \sum_{i=t+1}^{L} \hat{h}_{t;k}(x_{k-i} - \hat{x}_{k-i}) + \left( \sum_{i=0}^{P+L} \theta_{t;k} r_{k-i} - \sum_{i=t+1}^{L} \phi_{t;k} \hat{x}_{k-i} \right) + \eta_k \right|^2$$

(6.28)

The estimated noise variance from the hard decisions in the first stage is

$$\hat{\sigma}^2_n = \frac{1}{K} \sum_{k=1}^{K} \left| e(t_k^t | \hat{x}_k) - \hat{h}(t_k^t | \hat{x}_k)^T \hat{x} \right|^2$$

(6.29)

Expanding (6.29) using (6.24) and (6.25),

$$\hat{\sigma}^2_n = \frac{1}{K} \sum_{k=1}^{K} \left| \sum_{i=t+1}^{L} \hat{h}_{t;k}(x_{k-i} - \hat{x}_{k-i}) + \left( \sum_{i=0}^{P+L} \theta_{t;k} r_{k-i} - \sum_{i=t+1}^{L} \phi_{t;k} \hat{x}_{k-i} \right) + \eta_k \\
+ \sum_{i=0}^{L} \hat{h}_{t;k}(x_{k-i} - \hat{x}_{k-i}) \right|^2$$

(6.30)

$$\approx \sigma^2_n$$

The sensitivity of noise variance due to fast time-varying channel is illustrated in figure 6.11 where the extreme case of non adaptation is considered. For RA300 channel, at 10% BLER, the CSO-RSSE with 2 and 8 state Log-MAP requires a SIR in excess of 19.5 dB and 18 dB respectively while the 2 state SO-RSSE requires 18 dB. The cascaded 8 state Log-MAP fares worse than the RS-SSA and only manages to achieve similar performance to the 2 state SO-RSSE. Although the effect is milder for RA250 channel, the cascaded scheme still has a higher error floor than the single stage method. At SIR of 25 dB, the cascaded scheme with 2 state Log-MAP achieves a BLER of about 1.8%, while the 2 state SO-RSSE experiences only 1% BLER.

The main reason for the degradation is due to over-estimation of the noise variance in (6.29), when using final hard decisions from the first stage. The channel at the centre of the burst varies significantly towards the start and end of the time slot in a fast time varying channel. Therefore, without adaptation, the hard decisions become unreliable, which results in a large value in the last summation terms of (6.30), which
are significantly weighted by the first $\mu + 1$ taps of the TOCIR. Consequently, this error term contributes substantially to the overall path metric accumulated at the end of sequence estimation, thus leading to over-estimation, even though it is averaged over the sequence length where the noise variance is computed in (6.29). However, in moderate channels like TU50, the coherence time is about 12 ms for a 900MHz carrier frequency. This is about 20 times the burst duration (0.577ms) and is relatively long enough for a significant change in the fading behaviour and thus the channel can be considered safely as quasi-stationary.

In order to minimize the degradation, the noise variance is estimated using tentative decisions while employing hard decisions from the first stage as the decision feedback in the succeeding stage. Figure 6.12 and 6.13 shows two cases of improvement with noise variance estimated using the tentative path metric obtained at i) half the data sequence length; and ii) at the length TS respectively. In both cases, i) and ii), the CSO-RSSE with 2 state Log-MAP achieves a better performance than the 2 state SO-RSSE especially in the region of 10 dB to 20 dB. This region has a moderate SNIR and
therefore implies that the cascaded scheme is better able to reduce decision feedback error than the single stage. In i), the cascaded scheme with 8 state Log-MAP performs slightly better than the single stage scheme. Although the improvement may be modest (0.2 dB at 10% BLER), it has the advantage of reducing decision feedback error which allows to outperform the single stage methods in the various environments of chapter 5.

Figure 6.12: Sensitivity of Noise Variance Estimation Using Tentative Decisions at the middle of the Data Sequence

6.4.2 Performance of ACSO-RSSE over Fast Time-varying Frequency Selective Fading Channels

Figure 6.14 benchmarks the performance of the Adaptive cascaded scheme against the single stage method over a fast time-varying frequency selective fading channel. In RA250, the cascaded scheme outperforms the single stage scheme especially in the mid SIR region. Comparing the 2 state configuration, the cascaded approach is about 0.5dB better than the single stage at 10% BLER. However, a modest improvement of 0.2 dB is observed for the 8 state configuration. This again suggest that the cascaded scheme
6.4. Adaptive Two Stage Soft Decision Data Estimation

Figure 6.13: Sensitivity of Noise Variance Estimation Using Tentative Decisions at the end of Training Sequence

Figure 6.14: Performance of ACSO-RSSE
is more resistant to decision errors.

In RA300, which represents the scenario of a high speed train, the cascaded scheme fares similarly to the single stage in the mid SIR region. This is due to imperfect tracking of the parameters, which leads to less reliable final hard decisions and noise variance estimates. However, at high SIR, it has a much reduced error floor compared with the single stage. For 2% BLER, the cascaded 8 state scheme is about 1.4 dB better than ASO-DDFSE and ARS-SSA, while the 2 state cascaded scheme is 0.3 dB worse than the single stage.

The degradation can be compensated using tentative decisions estimated noise variance. As shown in the figure, estimating noise variance at the end of the TS, the 2 state cascaded scheme is able to achieve similar performance to the single stage. However, for the 8 state configuration, there are no significant changes in performance between the hard and tentative decisions estimated noise variance. It should be noted that the cascaded scheme with 2 state Log-MAP is more sensitive to noise variance due to its branch transition probability being obtained as a sum over its associated parallel branches. Nevertheless, the cascaded scheme with 2 state Log-MAP achieves similar performance to the ASO-DDFSE.

6.5 Complexity Analysis of Reduced State Soft Output Equalizers

As mentioned in the problem definition of chapter 1, optimum equalization using VA is far too complex for implementation in EDGE due to the huge trellis size required. Fortunately, sub-optimum reduced complexity schemes can be employed with an approximated optimum performance but at the cost of a pre-filter. Soft output schemes that offer improved detection reliability require additional computation effort. Finally, to cope with the fast time varying channel, parameters adaptation is necessary and can pose substantial strain on the DSP. Therefore an assessment of the complexity requirements is necessary.
6.5. Complexity Analysis of Reduced State Soft Output Equalizers

6.5.1 Components of Complexity

Trellis Size

The SSA and logarithmic BCJR MAP have been introduced and shown to be possible candidates for soft output equalization in EDGE. The DDFSE is applied to reduce the trellis size, $Z$, from $M^L$ to $M^H$ but at the cost of an additional pre-filter. The trellis size is further reduced by means of set-partitioning, where the RSSE is applied to the Log-MAP. Reducing the trellis size has a great impact on the overall complexity reduction. With a reduced trellis, it means that parameter tracking using PSP can be implemented at a lower cost.

Marginalization

Two marginalization operators, min, and max* are used in the current application. Each of the marginalization operators converts joint soft information on input-output pair like as the SSA (5.20) to marginal soft information on the conditional values of the symbols. The use of such operators depends on the type of soft output algorithm and has an impact on the computational complexity.

For Log-MAP, it is characterized by max*, which consists of a basic compare and add operation as shown in (5.13). It can be simplified by disregarding the correction factor in (5.13) and results in the Max-Log-MAP variant where the max is only needed for marginalization. Consequently, during a transition where $M$ paths enter a state, the recursion can be updated by the ACS operation as in the VA, except that min is employed.

Recursion and Delay

Recursion is a typical feature in symbol-by-symbol soft output algorithms. The idea is to evaluate soft outputs based on the soft information obtained in the previous symbol period. In order to improve the reliability of a decision, some algorithms like the SSA estimate only in the forward direction under the constraint of decision delay $D$. However, algorithms such as the BCJR require an additional backward recursion. This not only doubles the computation requirement in achieving the soft decision, additional
6.5. Complexity Analysis of Reduced State Soft Output Equalizers

comparisons and for \( M \) symbols, it requires \( M(Z - 1) \).

In logarithmic BCJR MAP, the basic operations can be generally characterized by the \( \text{max}^* \). Basically it comprised of a compare and add operation as in shown in (5.13). During the forward recursion in the transition \( s_k \rightarrow s_{k+1} \) in (5.9), there are \( M \) branches entering state \( s_{k+1} \), which requires marginalization. For \( Z \) states, it a total of \( Z(M - 1) \) such operations are executed. Likewise in the backward recursion, another \( Z(M - 1) \) \( \text{max}^* \) operations are necessary, which means a total of \( 2Z(M - 1) \) compare and add operations. Also, \( M \) additions per state is needed to update \( \alpha_k(s_k) \) in the forward pass as in (5.9), before being marginalized. This means \( 2ZM \) additions are needed for both the forward and backward recursions. In terms of memory usage, the Log-MAP and Max-Log-MAP needs buffering of all its branch transition probabilities for the backward recursions as well as storing \( \alpha_k(s_k) \) for each state while processing the backward recursion. The buffering costs a total of \( ZMK + ZK \) memory units.

The Max-Log-MAP shares identical buffering requirements as the Log-MAP but is more efficient computationally. A saving of \( 2Z(M - 1) \) is achieved by disregarding the correction term and the ACS can be used for recursion updates.

In comparison, the SSA has a smaller memory requirement than the Log-MAP given that both have the same trellis size. It is also computationally more efficient than the Log-MAP, provided that its decision delay \( D = \mu \). Assuming \( D = \mu \) and \( \mu = 1 \), the reduced state Log-MAP, Max-Log-MAP and the SSA requires 352, 240 and 120 ADD/CMP operations per trellis interval respectively. Generally, \( D = 5\mu \) is the practical delay being recommended for reasonably reliable survivors [13], and this require 3960 ADD/CMP operations that is 11 times more computationally intensive than Log-MAP even though both have the same amount of trellis. Consider the forward equalization process, the block length, \( K = 58 \). Both the MAP variants require 4176 memory units while the SSA requires only 224 memory units for \( D = 5\mu \). This suggests that BCJR MAP is suitable for short sequence lengths.

Complexity Reduction With RSSE

Applying set-partitioning to the symbol constellation, the trellis size requirements of BCJR MAP can be significantly reduced from \( Z = M^\mu \) to \( \prod_{i=1}^{\mu} J_i, J_1 > \cdots > J_\mu \).
Each transition branch is associated with \( M/J_1 \) parallel branches corresponding to each symbol in the subset. There will be \( J_1(M/J_1) \) parallel branches entering a subset state and requiring marginalization. For the update, it require \( J_1(M/J_1) \) additions and \( J_1(M/J_1) - 1 \) marginalization operations. This amount to \( 2Z(M/J_1)J_1 + 2(M - 1)Z \) additions and \( 2(M - 1) \) compare operations, which include both forward and backward passes and all subset states. Similarly, it is necessary to buffer the entire block of \( J_1(M/J_1) \) parallel branches and \( \alpha_k(s_k) \) for the backward pass, which results to \( Z(M + 1)K \) memory units. When \( J_1 = M, J_1 = \cdots = J_\mu = M \) the complexity of the RSSE reduced Log-MAP amounts identically to the requirements of Log-MAP with DDFSE as in table 6.1. Under such conditions the RSSE becomes the DDFSE [45]. In general these relationships also accounts for the complexity reduction with RSSE. Table 6.2 summarizes the complexity of Log-MAP with RSSE for various levels of set partitioning. It can be seen that increasing the set partition depth may have halved the overall complexity but its memory requirement still remains substantially higher than a 8 state SSA. Nevertheless, its low computation requirement is desirable, especially for the 2 state Log-MAP, which is highly suitable for DSP implementation.

<table>
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<td>240</td>
<td>120</td>
<td>60</td>
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<tr>
<td>( N_{CMP} )</td>
<td>112</td>
<td>56</td>
<td>28</td>
</tr>
<tr>
<td>( N_{MEM} )</td>
<td>5328</td>
<td>2664</td>
<td>1332</td>
</tr>
</tbody>
</table>

Table 6.2: Complexity Requirements of Log-MAP with RSSE \((M = 8, \mu = 1)\)

Complexity of Cascaded RSSE and Log-MAP

The two stage approach involves a hard decision RSSE and a Log-MAP in cascade, is suggested as an improvement over the various single stage soft output configurations (SO-RSSE and RS-SSA). It is therefore important to analyze its complexity.

The complexity of the hard decision RSSE can be summarized as follows. There are \( J_1 \) branches merging to each subset state \( t_k \). Each branch there are \( M/J_1 \) corresponding parallel branches, which require \( M \) additions and \( (M - 1) \) comparisons to determine the survivor metric for each state \( t_{k+1} \). In this case, the parallel branch with the minimum
6.5. Complexity Analysis of Reduced State Soft Output Equalizers

metric in the subset is selected. This requires 4 Euclidean distance computations. Due to the geometric symmetry in the subset definition, the signal points with minimum branch metric can be determined by simple slicing operations, as shown in figure 6.15 where the decision point that shares the same quadrant as the observation $r_k$ is selected. Therefore, only $J_1$ explicit branch metric computations will be necessary and that means $ZJ_1$ additions and $Z(J_1 - 1)$ comparisons are required per trellis interval. The memory required for storing survivor paths and the survivor metric is $ZK$ and $Z$ which is $(Z + 1)K$ in total.

![Figure 6.15: Decisions on Parallel Transitions](image)

Parameter tracking using PSP requires additional memory of $Z(L + 1)K$ and $Z(P + L + 1)K$ to store the coefficients of TOCIR and pre-filter respectively. During LMS update, $2Z(L + 1)$ multiply and $Z(P + L + 1)$ add operations are needed during the subset transition $t_k^\mu \rightarrow t_k^\mu$. The overall complexity of the first stage RSSE can be summarized as

<table>
<thead>
<tr>
<th>Complexity Requirements</th>
<th>Sequence Estimation</th>
<th>Parameters Tracking</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N_{ADD}$</td>
<td>$ZJ_1$</td>
<td>$Z(L + 1)$</td>
</tr>
<tr>
<td>$N_{CMP}$</td>
<td>$Z(J_1 - 1)$</td>
<td>$Z(P + L + 1)$</td>
</tr>
<tr>
<td>$N_{MPY}$</td>
<td>$\times$</td>
<td>$2Z(L + 1)$</td>
</tr>
<tr>
<td>$N_{MBM}$</td>
<td>$Z(K + 1)$</td>
<td>$Z(L + 1)K$</td>
</tr>
</tbody>
</table>

Table 6.3: Complexity Requirements of Hard Decision RSSE with PSP ($\mu = 1$)

Assume each compare operation is identical to the addition operation in complexity
while the multiply operation is equivalent to $q$ additions in a generic processor, the average computation complexity of the algorithms is defined as $(N_{ADD} + N_{CMP} + N_{MPY})$ units of computation per trellis interval. Using table 6.3, the 2 state RSSE requires $(50 + 88q)$ ADD/CMP/MPY including parameter tracking. The 8 and 2 state Log-MAP requires 352 and 88 ADD/CMP operations respectively. Hence on average, the cascaded scheme requires $(402 + 88q)$ and $(138 + 88q)$ units of computation for a 8 and 2 state Log-MAP.

For the adaptive RS-SSA, it requires $(294 + 352q)$ ADD/CMP operations just for parameter tracking, while 120 and 3960 ADD/CMP operations are required for $D = \mu$ and $D = 5\mu$ respectively, just to work out the soft decisions. This amounts to a total of $(414 + 352q)$ and $(4254 + 352q)$ ADD/CMP/MPY. The cascaded scheme requires an additional 2664 memory units while the RS-SSA needs a modest amount of 176 units for parameter tracking.

The complexity and performance of single stage schemes are directly dependent on the trellis size. However, the cascaded scheme de-couples the complexity of joint channel, pre-filter and soft output detection by incorporating parameter tracking in the first stage, where a low complexity RSSE can be utilized. As a result, the cascaded scheme can be justified for DSP implementation as follows:

i) Despite of its substantial memory requirements, it achieves superior performance through mitigating decision errors and improving noise estimation.

ii) It is less computation intensive than RS-SSA, as the number of multiplications required is considerably lower.

ii) The cascaded scheme with 2 state Log-MAP can also be utilized with much improved performance over the 2 state SO-RSSE. Furthermore, it has also been shown to perform better than the RS-SSA in many environments.

6.6 Summary and Conclusions

This chapter investigates a low complexity joint channel, pre-filter and soft output data estimation scheme for fast time-varying frequency selective fading channels such as the
scenario of a high speed train. Initially, a joint channel, pre-filter and data estimation scheme involving the RSSE of various complexity are developed to establish an adaptive structure that employs PSP and LMS algorithm for parameter update. It is shown that 2 state adaptive RSSE performs as well as the 8 state.

However, with soft output algorithms incorporated, the complexity and performance become tightly coupled. Reducing the trellis size may ease the computation requirements of adaptation but at the expense of performance degradation, such as in the case of a 2 state SO-RSSE. In such situations, the single stage, reduced state BCJR MAP variants offer little advantage to SSA. As before, the 2 state MAP variants suffered the most degradation due to decision errors and inaccurate noise estimation (for Log-MAP). Most important of all, the marginalization of parallel branches during a recursion update in the trellis results in somewhat an 'average' value that leads to less reliable decisions. The cascaded scheme is proposed to avoid these undesirable side effects by segregating the Log-MAP from parameter tracking. This is done by incorporating adaptation in the first stage with a low complexity RSSE. Despite its substantial memory requirements, it is shown to achieve superior performance by mitigating decision errors and improved noise estimation with a much lower computation effort than the RS-SSA. The most important issue is that the good performance of Log-MAP is preserved while the computation requirements of parameter tracking are simultaneously reduced.

Without adaptation, the two stage approach performs worse than the single stage. This is because the final hard decisions derived from the first stage become unreliable and lead to excessive over-estimation in the noise variance and increased decision errors. A simple approach using tentative decisions is proposed for noise variance estimation while maintaining final hard output for decision feedback in the second stage. It is also shown that with parameter tracking the overall sensitivity to noise variance estimation decreases.
Chapter 7

Conclusions and Future Work

This work has made several contributions that have resulted in the publications listed in Appendix D [16-18]. In the following sections the contributions of this work are summarized and concluded and areas for future research are suggested.

7.1 Conclusions

The optimum equalizer based on the VA is adopted in GSM but is too complex for implementation in EDGE. The VA’s complexity is exponential with the symbol size and the overall channel memory. In order to approximate the performance of the MLSE, a sequence estimation structure that involves the pre-filter and the 8 state DDFSE was proposed for EDGE initially. For further complexity reduction, the Ungerboeck set partitioning method was applied to the DDFSE and resulted in 4 and 2 states RSSE. The pre-filter transforms the OCIR into a minimum/maximum phase equivalent to suit the bi-directional equalization. The intention was to concentrate the channel taps towards the zero delay taps so that a significantly smaller trellis based on the first few taps of the TOCIR can be constructed with minimum complexity. With this technique, 2 state RSSE is shown to have similar performance to the 8 state DDFSE over the various GSM multi-path channels. Although the 8 state DDFSE is shown to be sufficient for EDGE in [9], the work reported here first demonstrated the possibility of
even lower reduced state RSSE as in [17]. This has been later confirmed by Gerstacker et al [19] with theoretical analysis.

Ideally, the pre-filter is essentially a WMF that has a infinite impulse response but for practical implementation, it is approximated by a FIR filter. The WF is obtained from \( P^{th} \) order LP [20]; [8,19] proposed to compute its coefficients using the LD algorithm. The current approach adopts a more computationally efficient method involving the Schur algorithm instead, where parallelism is exploited. The higher the order of the pre-filter, the better it approximates the ideal but at a higher cost in complexity. The effects of pre-filtering on the reduced state trellis equalizers are studied. A \( 15^{th} \) instead of a \( 25^{th} \) order pre-filter proposed by [8], is demonstrated in chapter 4 to be sufficient for coping with dispersive channels like the urban environment and channels with long impulse responses as in hilly terrain.

A practical, low complexity soft output data estimation scheme that employs the DDFSE to reduce the trellis size of the logarithmic BCJR MAP (Log-MAP and Max-Log-MAP) was proposed for equalization in EDGE. Additionally, the reduced state SSA employing the DDFSE was also developed as an option to BCJR MAP variants for complexity reduction. The Log-MAP outperforms the SSA significantly but requires higher complexity even though both employ the DDFSE for trellis reduction and have an identical number of trellis states. Although, the first soft output technique was first proposed in [21], it involves Lee's soft output algorithm [22] that delivers soft decisions in the probability domain, which is not desirable [13,14].

With set-partitioning, the BCJR MAP complexity was further reduced with RSSE. Although the 2 state Max-Log-MAP was shown in [19] as a possible candidate for soft equalization in EDGE, however, the current work addresses in detail, the impacts of reduced state on the performance of BCJR MAP variants. The results show that the 2 state BCJR MAP, which represents the extreme case of set partitioning, suffered the most performance degradation due to the summing of parallel branches, that leads to less reliable decisions when computing the bit log-likelihood values. Nevertheless, in chapter 5, these single stage schemes are shown to perform with comfortable implementation margins under noise limited environments associated with GSM multi-path
channel profiles. These results were later confirmed by [85].

The effect of interference limited channels on the reliability of the reduced state algorithms were evaluated. It is found that the 8 state Log-MAP is slightly better than the reduced state SSA. This implies that the Log-MAP is sensitive to mismatched noise which now consists of a mixture of thermal noise and co-channel interference for which the overall statistical distribution is unknown but is assumed to be Gaussian by the various reduced state soft output algorithms. They are also degraded by decision errors, which is an inherent problem when utilizing decision feedback to cancel the residual ISI resulting from data estimation with a smaller trellis.

Subsequently, an improved two stage approach that segregates the reduced trellis equalizer and the MAP estimator into two cascaded stages was developed. The cascaded scheme makes use of final hard decisions from the 2 state RSSE as feedback decisions, in contrast to the SO-DDFSE and SO-RSSE where the tentative decisions are employed. The noise variance is estimated from the final hard output, which uses a longer average over the data symbols and thus results in a more unbiased and accurate estimate. The cascaded schemes were studied along with the single stage soft output schemes. The cascaded 8 state Log-MAP is shown to surpass single stage schemes in interference limited environments as shown in chapter 5, with and without ideal frequency hopping, while the 2 state Log-MAP offers improvement over its single stage equivalent in some cases only. With improved noise variance estimation and reduced decision feedback errors, the cascaded method cannot avoid the degradation caused by trellis reduction using extreme set partitioning. Nevertheless, the cascaded 2 state Log-MAP is still an improvement over the the 2 state SO-RSSE for complexity reduction. Although, Zeng et al [23] proposed a similar cascaded method as an improvement to the single stage technique by [21], they employed the DDFSE in cascade with Lee's algorithm and assumed a quasi-stationary channel. The current method employs the RSSE in cascade with a Log-MAP, which has a lower complexity than [23]. In addition, the effects of fast time-varying channels are also investigated and good performances are reported in chapter 5.

The investigation proceeded to address a low complexity joint channel, pre-filter and
7.1. Conclusions

soft output data estimation structure for mitigating the adverse effects of fast time-varying frequency selective fading channels such as the scenario of a high speed train. Under such channel conditions, parameters tracking is necessary as they are derived during channel estimation from the centre of the burst, where the channel is fast time varying and unknown a priori. Although similar techniques has been used in [24–27] for adaptive equalization in GSM, they involve the MLSE algorithm. The work reported in the thesis employs reduced state algorithms with soft output incorporated and leads to a published work in [86].

Initially, a joint channel, pre-filter and data estimation scheme involving the RSSE of various complexity was developed to establish an adaptive structure that employs PSP and LMS algorithm for parameter updating. Two LMS update algorithms for the pre-filter and the TOCIR were developed by approximating the SD algorithm. With the adaptive structure, the 2 state adaptive RSSE is shown to perform as well as the 8 state over the GSM channel profile, which suggests that the 2 state RSSE is highly desirable for parameter tracking due its low complexity.

However, with a soft output algorithm incorporated, the complexity and performance become tightly coupled. Reducing the trellis size may ease the computation requirements of adaptation, but at the expense of performance degradation such as the case of a 2 state SO-RSSE. Under interference limited channels, the reduced state BCJR MAP variants offer little advantage to SSA as before. The 2 state MAP variants suffer the most degradation due to decision errors and inaccurate noise estimation (for Log-MAP). Most important of all, the marginalization of parallel branches during a recursion update in the trellis results in somewhat an 'average' value that leads to a less reliable decision.

The cascaded scheme was proposed as the strategy to avoid these undesirable side effects by segregating the Log-MAP from parameters tracking. First the overall complexity is de-coupled by deploying adaptation in the first stage with a low complexity RSSE (2 state). A higher order Log-MAP in the second stage is used to avoid the side effects of extreme set partitioning. Despite its overall substantial memory requirements, the cascaded scheme is shown to achieve superior performance by mitigating decision errors
and improved noise estimation with a much lower computation effort than the RS-SSA. The most important result is that the good performance of Log-MAP is preserved while the computation requirements of parameters tracking are simultaneously reduced.

Without adaptation, the two stage approach performs worse than the single stage. This is because the final hard decisions derived from the first stage become unreliable and lead to excessive over-estimation of the noise variance and increased decision errors. A simple approach using tentative decisions is proposed for approximating the noise variance while maintaining final hard output for decision feedback in the succeeding stage. The tentative noise estimation approach was further investigated with adaptation. The results suggest that with parameter tracking the overall sensitivity to noise variance estimation decreases.

Finally, the complexity requirements of both the single and cascaded schemes were evaluated and analyzed. The cascaded scheme requires substantial extra memory compared to the single stage RS-SSA, but considering the benefits of the two stage method in terms of better noise estimation, reduced decision errors, efficient parameter adaptation and superior performance, the two stage scheme seems superior to RS-SSA. However, when complexity is a major concern, the cascaded 2 state Log-MAP is concluded as the preferred choice for performance and complexity reduction, therefore suitable for implementation in EDGE.

7.2 Future Work

From the results of this work further work of research emerges as follows:

**Reduced Complexity Iterative Equalization for EDGE**

Iterative equalization by nature requires high complexity but offers a much better detection reliability than the non-iterative joint coding equalization scheme, allowing the former to operate at lower SNR. Therefore the performance of reduced state BCJR MAP variants could be improved by feeding back the decoder's extrinsic information to the soft output equalizer. With much reduced state schemes
such as the 2 state Max-Log-MAP, moderate increases in complexity can now be justified with optimized performance. Also, the proposed soft output schemes with various degrees of state reduction can be converted into an iterative type. As a result, the effects of reduced state on performance of various iterative soft output algorithms could be investigated. Lastly, adaptation can also be incorporated into iterative schemes which could find applications in high speed transportation (outside the EDGE specified requirements).

**Single Antenna Interference Cancellation for EDGE**

Handling of CCI is a difficult task as both the wanted channel and interferer lie in the same frequency band and cannot be separated by filtering. Although CCI can be suppressed using interference cancellation [10] and interference rejection techniques [11, 12], substantial computation is required, which is sometimes not easily available, as in the case of mobile handsets. Therefore, the proposed reduced state soft output techniques treat CCI as additive noise and makes the Gaussian assumption regarding the overall perturbation contribution, which includes both the thermal noise and CCI. However, it was not until very recently that the requirement and feasibility of interference cancellation for GSM has been addressed by the standardization body Third Generation Partnership Project [87, 88]. Therefore, the next step is to incorporate interference cancellation techniques into the proposed equalizers as joint reduced complexity equalization and interference cancellation schemes.
Appendix A

Linearized GMSK Pulse Shaping

The modulating 8-PSK symbols $x_k$ as represented by Dirac pulses excite a linear pulse shaping filter. This filter is a linearized GMSK pulse, comprised of Laurent decomposition of the GMSK modulation. The impulse response is expressed as:

$$C_0(t) = \begin{cases} \prod_{i=0}^{3} S(t+iT), & 0 \leq t \leq 5T \\ 0, & \text{else} \end{cases}$$  \hspace{1cm} (A.1)

$S(t)$ are the Laurent decomposition pulses given as

$$S(t) = \begin{cases} \sin(\pi \int_0^t g(t')dt'), & 0 \leq t \leq 4T \\ \sin\left(\frac{\pi}{2} - \pi \int_0^{t-4T} g(t')dt'\right), & 0 \leq t \leq 8T \\ 0, & \text{else} \end{cases}$$  \hspace{1cm} (A.2)

where $T$ is the symbol period and $g(t)$ is the Gaussian shaped frequency pulse of duration $4T$ given by

$$g(t) = \frac{1}{2T} \left[ Q\left(2\pi \cdot 0.3 \cdot \frac{t-5T/2}{T\sqrt{\ln 2}}\right) - Q\left(2\pi \cdot 0.3 \cdot \frac{t-3T/2}{T\sqrt{\ln 2}}\right) \right], 0 \leq t \leq 4T.$$  \hspace{1cm} (A.3)

and $Q(\cdot)$ denotes the complementary Gaussian error integral

$$Q(t) = \frac{1}{\sqrt{2\pi}} \int_t^\infty e^{-\frac{r^2}{2}} dr$$  \hspace{1cm} (A.4)
Appendix B

MAP Algorithms

B.1 BCJR MAP algorithm

In order to compute the a posteriori probability in (5.5), the following probabilities are defined:

\[ a_k(l) = \Pr(s_k = l; \bar{v}_1^{k-1}) \quad (B.1) \]
\[ \beta_{k+1}(l') = \Pr(\bar{v}_{k+1}^K | s_{k+1} = l') \quad (B.2) \]
\[ \gamma_k(l, l') = \Pr(s_{k+1} = l' | \bar{v}_k | s_k = l) \quad (B.3) \]

The joint probability, \( \Pr(s_k = l; s_{k+1} = l'| \bar{v}_1^K) \) is derived as

\[
\Pr(s_k = l; s_{k+1} = l'| \bar{v}_1^K) = \frac{\Pr(s_k = l; s_{k+1} = l'; \bar{v}_1^K)}{\Pr(\bar{v}_1^K)}
= \frac{\Pr(s_k = l; s_{k+1} = l'; \bar{v}_1^{k-1}; \bar{v}_k; \bar{v}_{k+1}^K)}{\Pr(\bar{v}_1^K)}
= \frac{\Pr(\bar{v}_1^{k-1} | s_k = l; s_{k+1} = l'; \bar{v}_1^{k-1}; \bar{v}_k) \Pr(s_k = l; s_{k+1} = l'; \bar{v}_1^{k-1}; \bar{v}_k)}{\Pr(\bar{v}_1^K)}
\quad (B.4)
\]

Because of the Markov property of the finite state machine model for the channel, knowledge of the state at time \( k + 1 \) supersedes knowledge of the state at time \( k \), and
it also supersedes knowledge of $\bar{y}_k$ and $\bar{y}_{k-1}^k$, so that (B.4) reduces to:

$$
Pr(s_k = l; s_{k+1} = l'|\bar{y}_{k}^k) = \frac{Pr(\bar{y}_{k+1}^K|s_{k+1} = l')Pr(s_k = l; s_{k+1} = l'; \bar{y}_1^{k-1}; \bar{y}_k)}{Pr(\bar{y}_1^{k})}
$$

$$
= \frac{Pr(\bar{y}_{k+1}^K|s_{k+1} = l')Pr(s_{k+1} = l'; \bar{y}_k|s_k = l; \bar{y}_1^{k-1})Pr(s_k = l; \bar{y}_1^{k-1})}{Pr(\bar{y}_1^{k})}
$$

$$
= \frac{Pr(s_k = l; \bar{y}_1^{k-1})Pr(s_{k+1} = l'; \bar{y}_k|s_k = l)Pr(\bar{y}_{k+1}^K|s_{k+1} = l')}{Pr(\bar{y}_1^{k})}
$$

$$
= \alpha_k(l)\gamma_k(l,l')\beta_{k+1}(l')
$$

Derivation of $\alpha$

$$
\alpha_{k+1}(l') = Pr(s_{k+1} = l'; \bar{y}_1^{k})
$$

$$
= Pr(s_{k+1} = l'; \bar{y}_1^{k-1})
$$

$$
= \sum_{l=0}^{Z-1} Pr(s_k = l; s_{k+1} = l'; \bar{y}_1^{k-1})
$$

$$
= \sum_{l=0}^{Z-1} Pr(s_{k+1} = l'; \bar{y}_k|s_k = l; \bar{y}_1^{k-1})Pr(s_k = l; \bar{y}_1^{k-1})
$$

$$
= \sum_{l=0}^{Z-1} Pr(s_{k+1} = l'; \bar{y}_k|s_k = l)Pr(s_k = l; \bar{y}_1^{k-1})
$$

$$
= \sum_{l=0}^{Z-1} \gamma_k(l,l')\alpha_k(l) \quad (B.5)
$$

Derivation of $\beta$

$$
\beta_k(l) = Pr(\bar{y}_1^{K}|s_k = l)
$$

$$
= Pr(\bar{y}_k; \bar{y}_{k+1}^K|s_k = l)
$$

$$
= \sum_{l'=0}^{Z-1} Pr(\bar{y}_k; \bar{y}_{k+1}^K|s_{k+1} = l'|s_k = l)
$$

$$
= \sum_{l'=0}^{Z-1} Pr(\bar{y}_{k+1}^K|\bar{y}_k; s_{k+1} = l'|s_k = l)Pr(\bar{y}_k; s_{k+1} = l'|s_k = l)
$$

$$
= \sum_{l'=0}^{Z-1} Pr(\bar{y}_{k+1}^K|s_{k+1} = l')Pr(\bar{y}_k; s_{k+1} = l'|s_k = l)
$$

$$
= \sum_{l'=0}^{Z-1} \gamma_k(l,l')\beta_{k+1}(l') \quad (B.6)
$$
B.2 Lee MAP algorithm

The transmitted complex valued symbol at time, \( k \) are denoted by \( x_k \in \{X^0, \cdots, X^{M-1} \} \) where \( M \) symbol constellation size. The transmitted signal over an ISI channel and corrupted by AWGN as described in chapter 3, are observed as \( \tilde{v}_k \). The objective of Lee’s MAP algorithm [22] is to compute the \( M \)-ary information packet, \( \{Pr(x_k = X_j|\tilde{v}_k^{k+D})\}_{j=0,\ldots,M-1} \) containing the estimates for the APP under the constraints of a fixed decision delay, \( D \), requiring only forward recursion. The APP, \n\[
Pr(x_k|\tilde{v}_k^{k+D}) = \frac{Pr(x_k;\tilde{v}_1^{k+D};s_k+D+1)}{Pr(\tilde{v}_1^{k+D};s_k+D+1)} \tag{B.7}
\]
can be expressed as summation over all state of joint probabilities as
\n\[
Pr(x_k|\tilde{v}_1^{k+D}) = \sum_{s_k+D+1} Pr(x_k;\tilde{v}_1^{k+D};s_k+D+1) \frac{Pr(\tilde{v}_1^{k+D};s_k+D+1)} {\sum_{s_k+D+1} Pr(\tilde{v}_1^{k+D};s_k+D+1)} \tag{B.8}
\]

Two recursive formulas are required to solve the numerator and denominator of B.8 as shown in the following:

**First Recursion** For \( k, k > 1 \)
\n\[
Pr(\tilde{v}_1^k; s_{k+1}) = \sum_{s_k} Pr(\tilde{v}_1^k; s_k; s_{k+1})
\]
\[
= \sum_{s_k} Pr(\tilde{v}_1^{k-1}; \tilde{v}_k; s_k; s_{k+1})
\]
\[
= \sum_{s_k} Pr(\tilde{v}_1^{k-1}; s_k) Pr(\tilde{v}_k; s_{k+1}|\tilde{v}_1^{k-1}; s_k)
\]
\[
= \sum_{s_k} Pr(\tilde{v}_1^{k-1}; s_k) Pr(\tilde{v}_k; s_{k+1}|s_k)
\]
\[
= \sum_{s_k} Pr(\tilde{v}_1^{k-1}; s_k) Pr(\tilde{v}_k|s_{k+1}; s_k) Pr(s_{k+1}|s_k) \tag{B.9}
\]

**Second Recursion** For \( 1 \leq d \leq D \),
\n\[
Pr(x_k; \tilde{v}_1^{k+d}; s_{k+d+1}) = \sum_{s_{k+d}} Pr(x_k; \tilde{v}_1^{k+d-1}; \tilde{v}_{k+d}; s_{k+d+1}; s_{k+d})
\]
\[
= \sum_{s_{k+d}} Pr(\tilde{v}_{k+d}; s_{k+d+1}|x_k; \tilde{v}_1^{k+d-1}; s_{k+d}) Pr(x_k; \tilde{v}_1^{k+d-1}; s_{k+d})
\]
\[
= \sum_{s_{k+d}} Pr(\tilde{v}_{k+d}|s_{k+d+1}; s_{k+d}) Pr(x_k; \tilde{v}_1^{k+d-1}; s_{k+d}) \tag{B.10}
\]
The initial value of this recursion (B.10) is

$$Pr(x_k; \hat{o}^k_1; s_{k+1}) = Pr(\hat{o}^k_1; s_{k+1}) Pr(x_k|\hat{o}^k_1; s_{k+1})$$

$$= \begin{cases} 
Pr(\hat{o}^k_1; s_{k+1}), & \text{if } x_k \text{ is the first digit of } s_{k+1} \\
0, & \text{otherwise}
\end{cases}$$

(B.11)
Appendix C

GSM Wideband Propagation Profile

<table>
<thead>
<tr>
<th>Tap</th>
<th>Delay (μS)</th>
<th>Power (dB)</th>
<th>Doppler Spectrum</th>
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</thead>
<tbody>
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<td>1</td>
<td>0.0</td>
<td>0.0</td>
<td>Rice</td>
</tr>
<tr>
<td>2</td>
<td>0.1</td>
<td>-4.0</td>
<td>Classical</td>
</tr>
<tr>
<td>3</td>
<td>0.2</td>
<td>-8.0</td>
<td>Classical</td>
</tr>
<tr>
<td>4</td>
<td>0.3</td>
<td>-12.0</td>
<td>Classical</td>
</tr>
<tr>
<td>5</td>
<td>0.4</td>
<td>-16.0</td>
<td>Classical</td>
</tr>
<tr>
<td>6</td>
<td>0.5</td>
<td>-20.0</td>
<td>Classical</td>
</tr>
</tbody>
</table>

Table C.1: Typical case for Rural area (RA): 6 tap setting
<table>
<thead>
<tr>
<th>Tap</th>
<th>Delay (µS)</th>
<th>Power (dB)</th>
<th>Doppler Spectrum</th>
</tr>
</thead>
<tbody>
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<td>Classical</td>
</tr>
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<td>-6.0</td>
<td>Classical</td>
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<tr>
<td>6</td>
<td>5.0</td>
<td>-10.0</td>
<td>Classical</td>
</tr>
</tbody>
</table>

Table C.2: Typical case for Urban area (TU): 6 tap setting

<table>
<thead>
<tr>
<th>Tap</th>
<th>Delay (µS)</th>
<th>Power (dB)</th>
<th>Doppler Spectrum</th>
</tr>
</thead>
<tbody>
<tr>
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<td>0.0</td>
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<td>6</td>
<td>17.2</td>
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Table C.3: Typical case for Hilly Terrain (HT): 6 tap setting

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<th>Tap</th>
<th>Delay (µS)</th>
<th>Power (dB)</th>
<th>Doppler Spectrum</th>
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<td>1</td>
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<td>16.0</td>
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Table C.4: Equalizer Test profile (Eq): 6 tap setting
Appendix D

List of Publications

Journal Papers


Conference Papers


# Glossary

## Acronyms

<table>
<thead>
<tr>
<th>Acronym</th>
<th>Description</th>
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<tr>
<td>2G</td>
<td>Second Generation</td>
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<td>Third Generation</td>
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<td>Adjacent Channel Interference</td>
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<td>ACS</td>
<td>Add-Compare-Select</td>
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<td>ACSO-DDFSE</td>
<td>Adaptive Cascaded Soft-output Delayed Decision Feedback Sequence Estimation</td>
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<td>ACSO-RSSE</td>
<td>Adaptive Soft-output Reduced State Sequence Estimation</td>
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<td>A Posteriori Probability</td>
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<td>AWGN</td>
<td>Additive White Gaussian Noise</td>
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<td>BCJR</td>
<td>Bahl, Cocke, Jelinek and Raviv</td>
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<td>BER</td>
<td>Bit Error Rate</td>
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<td>BLER</td>
<td>Block Error Rate</td>
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<td>BS</td>
<td>Base Station</td>
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<td>Term Description</td>
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<td>------------------</td>
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<td>CCI</td>
<td>Co-Channel Interference</td>
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<td>CIR</td>
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<td>Circuit Switched Data</td>
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<td>Cascaded Soft-output Reduced State Sequence Estimation</td>
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<td>DDFSE</td>
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<td>DFE</td>
<td>Decision Feedback Equalizer</td>
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<td>DQPSK</td>
<td>Differential Quadrature Phase Shift Keying</td>
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<td>DSP</td>
<td>Digital Signal Processor</td>
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<td>ECSD</td>
<td>Enhanced Circuit Switched Data</td>
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<tr>
<td>EDGE</td>
<td>Enhanced Data Rates for GSM Evolution</td>
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<td>EDS</td>
<td>Exact Doppler Spread</td>
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<td>EGPRS</td>
<td>Enhanced General Packet Radio Service</td>
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<td>EQ</td>
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<td>FH</td>
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<td>GSM/EDGE Radio Access Network</td>
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<td>GSM</td>
<td>Global System for Mobile Communication</td>
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<td>Full Form</td>
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<td>IIR</td>
<td>Infinite Impulse Response</td>
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<td>IP</td>
<td>Internet Protocol</td>
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<td>IR</td>
<td>Incremental Redundancy</td>
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<td>ISI</td>
<td>Inter-Symbol Interference</td>
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<td>LA</td>
<td>Link Adaptation</td>
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<td>LD</td>
<td>Levinson-Durbin</td>
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<td>LE</td>
<td>Linear Equalizer</td>
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<td>Linearized Gaussian Minimum Shift Keying</td>
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<td>LLR</td>
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<td>LMS</td>
<td>Least Mean Square</td>
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<td>LP</td>
<td>Linear Prediction</td>
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<td>LS</td>
<td>Least Square</td>
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<td>MAP</td>
<td>Maximum A Posteriori</td>
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<td>MS</td>
<td>Mobile Station</td>
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<td>Description</td>
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<tr>
<td>MSE</td>
<td>Minimum Square Error</td>
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<td>MSP</td>
<td>Minimum Survivor Processing</td>
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<td>OCIR</td>
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<tr>
<td>OSA</td>
<td>Optimum Soft Output Algorithm</td>
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<tr>
<td>PBP</td>
<td>Per-Branch Processing</td>
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<td>Phase Shift Keying</td>
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<td>PSP</td>
<td>Per-Survivor Processing</td>
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<tr>
<td>QAM</td>
<td>Quadrature Amplitude Modulation</td>
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<tr>
<td>RA</td>
<td>Rural Area</td>
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<td>RLC</td>
<td>Radio Link Control</td>
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<td>RRC</td>
<td>Root Raised Cosine</td>
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<td>RS-SSA</td>
<td>Reduced State Suboptimum Soft-output Algorithm</td>
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<td>SA</td>
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<td>SINR</td>
<td>Signal-to-Interference-plus-Noise Ratio</td>
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<td>Soft-In/Soft-Out</td>
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</table>
SOVA  Soft-output Viterbi Algorithm
SRC   Square Root Raised Cosine
SSA   Suboptimum Soft-output Algorithm
TCM   Trellis Coded Modulation
TDMA  Time Division Multiple Access
TOCIR Transformed Overall Channel Impulse Response
TS    Training Sequence
TU    Typical Urban
UMTS  Universal Mobile Telecommunications System
VA    Viterbi Algorithm
VE    Viterbi Equalizer
WCDMA Wideband Code Division Multiple Access
WF    Whitening Filter
WMF   Whitened Matched Filter
ZFE   Zero Forcing Equalizer

Signals, Systems, Algebra

\((\cdot)^*\) Complex conjugate
\((\cdot)^H\) Vector or matrix complex conjugate transpose
\((\cdot)^T\) Vector or matrix transpose
\((l \rightarrow l')\) state transitions e.g. \(l\) to \(l'\)
\(\approx\) approximately equal
\(\delta(\cdot)\) Kronecker delta function
\( \Lambda(\cdot) \) log-likelihood function

\( \ln(\cdot) \) the natural logarithm function

\( \otimes \) Convolution

\( \bar{a}_k(l) \) forward recursion of BCJR MAP at epoch \( k \), state \( l \)

\( \bar{\beta}_k(l) \) backward recursion of BCJR MAP at epoch \( k \), state \( l \)

\( \bar{\gamma}_k(l,l') \) branch transition probability connecting state \( l \) to \( l' \) at epoch \( k \)

\( \propto \) proportional to

\( \sigma_n^2 \) variance of random variable \( n \)

\( \Delta \) equality by definition

\( e^{(\cdot)} \) the exponential function

\( E_b(E_s) \) energy per bit (symbol)

\( L \) Memory of OCIR

\( N_0 \) Single-sided noise power spectral density (Watts/Hz)

\( Pr(\cdot) \) probability of an event

\( s_k \) hyperstate of DDFSE at epoch \( k \)

\( t_k' \) subset state of RSSE (truncated to length \( \mu \)) at epoch \( k \)

\( t_k \) subset state of RSSE at epoch \( k \)

**Typefaces**

blackboard upper case set e.g. \((\mathbb{Q})\)

bold lower case column vector e.g., \((v)\)

bold upper case matrix e.g., \((V)\)
<table>
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<tr>
<th>Units</th>
<th>Definition</th>
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<td>dB</td>
<td>decibel</td>
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<tr>
<td>kbps</td>
<td>$10^3$ Bits per second</td>
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<tr>
<td>kHz</td>
<td>$10^3$ Hertz</td>
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<tr>
<td>km/h</td>
<td>$10^3$ metre per hour</td>
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<tr>
<td>ms</td>
<td>$10^{-3}$ Seconds</td>
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References


[7] ETSI, Digital cellular telecommunications(Phase2+);General Packet Radio Service(GPRS); Overall Description of the GPRS Radio Interface; stage 2 3GPP TS 09.64 Version 8.1.10, Release 1999.

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References


[77] ETSI, *Digital cellular telecommunications (Phase 2+); Modulation GSM 05.04 version 7.1.0*, Release 1998.


[79] ETSI, *Digital cellular telecommunications (Phase 2+); Multiplexing and Multiple Access on the Radio Path GSM 05.02 version 8.2.0*, Release 1999.

[80] ETSI, *Digital cellular telecommunications (Phase 2+); Radio transmission and reception GSM 05.05 version 8.5.1*, Release 1999.


