SPACE-TIME PROCESSING
FOR
WIRELESS MOBILE COMMUNICATIONS

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Abstract

Intersymbol interference (ISI) and co-channel interference (CCI) are two major obstacles to high speed data transmission in wireless cellular communications systems. Unlike thermal noise, their effects cannot be removed by increasing the signal power and are time-varying due to the relative motion between the transmitters and receivers. Space-time processing offers a signal processing framework to optimally integrate the spatial and temporal properties of the signal for maximal signal reception and at the same time, mitigate the ISI and CCI impairments. In this thesis, we focus on the development of this emerging technology to combat the undesirable effects of ISI and CCI.

We first develop a convenient mathematical model to parameterize the space-time multipath channel based on signal path power, directions and times of arrival. Starting from the continuous time-domain, we derive compact expressions of the vector space-time channel model that lead to the notion of *block space-time manifold.* Under certain identifiability conditions, the noiseless vector-channel outputs will lie on a subspace constructed from a set of basis belonging to the *block space-time manifold.* This is an important observation as many high resolution array processing algorithms can be applied directly to estimate the multipath channel parameters.

Next we focus on the development of semi-blind channel identification and equalization algorithms for fast time-varying multipath channels. Specifically, we develop space-time processing algorithms for wireless TDMA net-

works that use short burst data formats with extremely short training data sequences. Due to the latter, the estimated channel parameters are extremely unreliable for equalization with conventional adaptive methods. We approach the channel acquisition, tracking and equalization problems jointly, and exploit the richness of the inherent structural relationship between the channel parameters and the data sequence by repeated use of available data through a forward-backward optimization procedure. This enables the fuller exploitation of the available data. Our simulation studies show that significant performance gains are achieved over conventional methods.

In the final part of this thesis, we address the problem identifying and equalizing multipath communication channels in the presence of strong CCI. By considering CCI as stochasic processes, we find that temporal diversity can be gained by observing the channel outputs from a tapped delay line. Together with the assertion that the finite alphabet property of the information sequences can offer additional information about the channel parameters and the noise-*plus*-covariance matrix, we develop a spatial temporal algorithm, *iterative reweighting alternating minimization*, to estimate the channel parameters and information sequence in a weighted least squares framework. The proposed algorithm is robust as it does not require knowledge of the number of CCI nor their structural information. Simulation studies demonstrate its efficacy over many reported methods.

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Chapter 1

Introduction

Wireless communications methods and services have been actively pursued and adopted by people throughout the world. In the past ten years, wireless mobile communications have experienced phenomenal growth fueled by a combination of novel communications concepts and advances in signal processing, RF circuits fabrication and VLSI technologies. Coupled with the liberalization of the wireless markets in many countries, wireless communications systems are currently witnessing rapid growth in the number of users and proliferation in the range of services. Based on current trends and market forecast, the number of users is expected to be more then 590 millions by 2001 offering a wider variety of services such as wireless computing, multimedia, Internet, etc.

The radio spectrum allocation has recently been increased. However, it remains a limited resource. With the increasing demand for higher data rates, many wireless communications systems with their present spectral efficiencies are expected to be conjested to their capacities in the near future. This poses a major challenge for researchers and developers in wireless technology to develop novel system concepts and techniques aimed to improve spectral efficiency and achieve high capacity within a limited spectrum.

The cellular concept is a major breakthrough in improving the spectral efficiency within a limited spectrum allocation. It is a system level concept whereby the geographical coverage area is split into cells. Instead of using a high power transmitter to service the whole coverage area, the coverage in each cell is provided by a low power transmitter. Each cell uses a subset of available channel frequencies that is different from the neighbouring cells. The channel frequencies are carefully allocated to minimize co-channel and adjacent channel interference. Cells that are spatially far apart can reuse the channel frequencies. This notion of frequency reuse plays a key role that significantly improves the spectral efficiency of wireless communications systems. Recent advances such as cell splitting, sectoring and coverage zone, have been made in cellular design techniques to improve the capacity in the cellular systems. Together with multiple access techniques such as FDMA, TDMA and CDMA, wireless mobile networks provide users with the ability to communicate with other users connected to both fixed and mobile users.

In many wireless mobile communications systems, the radio propagation channels are extremely hostile. The signal travels from the transmitter to the receiver through a multipath channel, whereby the signal undergoes multi-reflections arriving at the receiver as a superposition of scaled and delayed versions of the transmitted waveforms. The relative motion between the transmitter, receiver and reflectors results in doppler shifts in the signal components, hence rendering the mobile propagation channel to be time-varying. Depending on the transmission rates and the channel dynamics, the effects of multipath can result in flat or frequency selective fading. The former results in loss of SNR while the latter results in delay spread that manifests as intersymbol interference (ISI).

Intersymbol interference (ISI) and co-channel interferences (CCI) are two major obstacles to high speed data transmission in wireless TDMA networks. Geometrically, the presence of ISI and CCI reduces the noise margin. Under extreme conditions (*e.g.* non-minimum phase channels), the transmitted symbols become indistinguishable leading to extremely poor error performance. Unlike thermal noise, these effects cannot be removed by increasing the signal power. Particularly, in an interference limited signal environment, increasing the signal power in one cell will increase the level of co-channel and adjacent channel interferences. These effects can be mitigated and controlled somewhat by careful frequency planning and allocation. However, they usually lead to poorer cell reuse factor resulting in poorer spectral efficiency.

1.1 Space-Time Processing for Wireless Communications

A promising approach to achieve substantial capacity gain in wireless cellular networks is the use of a multi-antenna array in the space-time processing framework. By processing the received signals in the space-time framework, both the spatial and temporal signal properties can be optimally integrated to maximize signal reception as well as to mitigate the channel impairments such as ISI and CCI.

Spatial processing can offer two leverages. Array signal processing algorithms such as digitial beamforming achieve directivity towards the signal of interest. This results in signal to noise ratio(SNR) improvement from the antenna gain. In addition, the spatial diversity of the antenna arrays can be used to discriminate and suppress multipath and co-channel interferences by forming nulls towards their directions of arrival. The usefulness of array signal processing in communication applications was recently demonstrated in many independent field trials [4] [5] [6] [7].

The inherent temporal structure of digital communication signals can be exploited to mitigate the effects of ISI and CCI. In general, digital communications signals exhibit temporal signal properties such as cyclostationarity, finite alpabet, constant modulus and higher order statistics. These temporal signal properties can provide deterministic and stochastic structures to identify the channel parameters and recover the transmitted waveforms as shown in [3] [20] [19] [22].

Processing the received signals in the space-time framework can optimally exploit both the spatial and temporal signal properties to maximize signal reception as well as to mitigate channel impairments. Recently, significant research effort has been focused on the development of space-time processing for wireless communications. In [22], spatial diversity and cyclostationarity of the oversampled received signals are used in blind identification of the channel parameters. Space-time constant modulus and space-time higher order statistic approaches were studied and proposed in [19] [3]. Algorithms for blind identification of multiple FIR channels were proposed in [39] [59]. These algorithmic approaches have been developed based on different assumptions and assertions on the signal and interference environment, temporal structures and channel dynamics.

In most engineering practices, it is not likely to develop a generic solution that solves all the air-interface problems. A thorough understanding of the signal environment and critical analysis of the requirements of the air-interface are necessary for the development of useful space-time processing algorithms. The focus of this thesis is to develop space-time processing algorithms for high speed data transmission in wireless TDMA networks. The main requirements of such algorithms are discussed next.

1.1.1 Analysis of Requirements of Space-Time Processing Algorithms for TDMA Networks

The applications of space-time algorithms to cellular mobile TDMA communication systems are often complicated by the fact that they need to operate in uncertain channel environments. The sources of uncertainties are due to the lack of precise knowledge of the channel and interference parameters and their variability with time. Broadly speaking, operating in uncertain channel environments involves acquisition and tracking. Acquisition is a transient process where the channel parameters are estimated. Tracking is a steady state process wherein the statistical variations of the channel parameters are tracked from an accurate initial estimate of the time-varying channel parameters.

The design of space-time algorithms for highly spectrum-efficient wireless TDMA networks is faced with a number of *competing* requirements. Good initial estimates of the channel parameters are spectrally expensive to acquire. It entails reserving a portion of the data sequence for non-blind channel estimation. Due to the presence of noise, reducing the training length will result in noisier initial estimates. This can induce detection errors due to poor tracking, particularly at the initial tracking phase. In GSM and IS-54 standards for wireless TDMA networks, more than 15% of their time-slots are reserved for training the channel equalizer. Clearly, the spectral efficiency of these networks can be significantly improved if the training sequence can be completely or significantly shortened while achieving reliable data transmission.

If time-invariance is assumed for on time-varying channels, modelling errors will be introduced. This can lead to poor sequence detection, particularly for rapidly time-varying channels. One way to deal with time-variance is to approximate the channel by contiguous segments of a quasi-stationary channel. wherein each data sub-block is independently processed. This is suboptimal as the full information residing within the data block is not exploited. Moreover, resolving the competing requirements of having large sub-block size and containing modelling errors remained open.

Most wireless TDMA networks use short burst data formats. For example. GSM and IS-54 time-slots are equivalent to 148 and 150 symbols, respectively. In addition to achieving multiple access, transmitting in time-slots of appropriate length can increase the possibility of facing fewer deep fades. As the time-slots are extremely short, the space-time processing algorithms must be data efficient and fast converging in order to combat the channel impairments within a very short period.

As remarked earlier, the price paid for frequency reuse is the introduction of co- and adjacent channel interferences. Increasing the signal power does not help as the increase of signal power in one cell will increase the level of co-channel and adjacent channel interferences. Hence, the space-time processing algorithms are expected to be robust to CCI/ACI while achieving reliable data transmissions at relatively low SNR.

In this development, we aim to develop the space-time processing algorithms for TDMA networks that:

- achieve good channel identification and equalization with minimal number of training samples ($= 2L - 1$, where L is the channel length), and able to rapidly converge and achieve reliable channel identification and equalization with burst data format (< 100 symbols).
- able to track and equalize low SNR ($< 10dB$) time-varying channels with large doppler spread ($> 300Hz$).
- achieve reliable channel identification and equalization at low signal to interference ratio ($< 7dB$).

1.2 About this Thesis

This thesis is divided into three parts. The first part, Chapters 2 and 3, formulates the space-time multipath propagation model and derives algorithms for estimating the multipath channel parameters. The second part, Chapter 4, addresses the problem of identifying time-varying multipath channels with extremely short training sequences. Finally, the third part in Chapter 5 addresses the problems of identification of multipath channels and sequence detection in the presence of strong interferers.

1.3 Thesis Contributions

The main contributions made in this thesis are as follows:

1. Introduction of a space-time channel model that reveals the underlying structure of the multipath propagation channel in terms of signal path power, directions and times of arrival. This model facilitates computer simulations to examine the performance and characteristics of the proposed algorithms under different propagation conditions.

2. Introduction of the notion of space-time manifold and formulation of the framework for the estimation of directions and times of arrival of multipath signals.

3. Derivation of Maximum Likelihood, MUSIC and Weighted Subspace Fitting algorithms for estimation of directions and times of arrival of multipath signals.

4. Introduction to the concept of time-reversal and formulation of a computationally and data efficient block-based semi-blind adaptive approach to least squares channel identification and sequence detection

of time-varying multipath propagation channels.

5. Formulation of a new approach to channel identification and equalization in the presence of strong co-channel interference.

Parts of the original work presented in this thesis have also been published or currently under review at various international journals and conferences:

1. C.M.S. See and C.F.N. Cowan, "Methods for Fast Blind Identification and Equalization of Communication Channels", *IEEE International Conference on Acoustics, Speech and Signal Processing*, Munich, April 1997.

2. C.M.S. See. "Fast and Data Efficient Approach to Blind Channel Identification and Equalization", *IEEE International Conference on Information, Communications and Signal Processing*, Singapore, Nov., 1997.

3. C.M.S. See and C.F.N. Cowan, "A Forward Backward Approach to Adaptive Space-Time Identification and Equalization of Time-Varying Channels". *IEEE International Conference on Acoustics, Speech and Signal Processing*, Seattle, May 1998.

4. C.P. Chua. C.M.S. See and A. Nehorai, "Vector-Sensor Array Processing for Estimating Angles and Times of Arrival of Multipath Communications Channel", *IEEE International Conference on Acoustics, Speech and Signal Processing*, Seattle, May 1998.

5. C.M.S. See and A. Nehorai, "Estimation of Directions and Times of Arrival of Multipath Signals Using a Calibrated Space-Time Antenna

Array", 9^{th} *IEEE Signal Processing Society Workshop on Statistical Array and Signal Processing*, Oregan, Sep. 1998.

6. C.M.S. See, A. Nehorai and C.F.N. Cowan, "Spatial Temporal Channel Identification and Equalization in the presence of Strong CCI" (**Invited Paper**), 34^{th} *Asilomar Conference on Signals, Systems and Computers*, Nov. 1998.

7. C.M.S. See and C.F.N. Cowan, "Adaptive Algorithms for Identification and Equalization of Time-Varying Channels", *IEEE International Conference on Communications, Singapore*, Nov. 1998.

8. C.M.S. See and C.F.N. Cowan, "Adaptive Algorithms for Identification and Equalization of Time-Varying Channels", *to appear in Proc. IEE Communications.*

9. C.M.S. See and C.F.N. Cowan, "Spatio-Temporal Channel Identification and Equalization in the Presence of Strong Co-Channel Interference" *to appear Eur. Signal Processing, Vol. 78.*

Chapter 2

Vectorized Space-Time Channel Model for Mobile Communications

The objective of this chapter is to formulate a convenient space time model for time-varying multipath channel in wireless mobile communications.

The original work in this chapter is threefold:

1. formulation of a space-time channel model that is parametrized by the signal path power, directions and times of arrival.

2. derivation of compact expressions for the space-time channel model and introducing the notion of space-time array manifold.

3. relating the derived space-time channel models to conventional space-time models.

2.1 Space-Time Channel Models

The complex representation of a linear modulated signal is given by

$$u(t) = \sum_{i=-\infty}^{\infty} s_i g(t - iT_b) \tag{2.1}$$

where $s_i \in \Omega$, $g(t)$ is the signal pulse shape and T_b is the symbol duration..

2.1.1 Discrete-Source Model

In this chapter, we develop a digital time-varying communications channel model by starting from the physical model. In the mobile communications environment, the signals emanating from the transmitting antenna undergo transformation due to reflection, diffraction and scattering. The received signal in the continuous domain (CT) can be modelled mathematically by

$$x(t) = \sum_{i=0}^{\mathbf{I}} a_i(t) u(t - \tau_i(t)) \exp(-j(\omega\tau_i(t) + \theta_i(t))) + n(t) \tag{2.2}$$

where $a_i(t)$ and $\tau_i(t)$ are the path gain and delay of the i^{th} path. ω is the carrier frequency (in radians) and $\theta_i(t)$ is a random phase with uniform distribution over $(0, 2\pi]$. $g(t)$ is the combined transmitter and receiver filter impulse response. I is the number of sources observable by the receiving system.

Extending the CT model (2.2)to a m sensors receiving system[1], we have

$$\check{\mathrm{x}}(t) = \sum_{i=0}^{\mathbf{I}} \mathrm{a}(\theta_i)\beta_i(t) \sum_{l=0}^{L} g(t - lT_b - \tau_i(t)) s_l + \check{\mathrm{n}}(t) \tag{2.3}$$

[1]The narrowband requirement of $\frac{d \times \omega_{BW}}{c} << 1$ is assumed; where d is the aperture of the antenna array, ω_{BW} is the signal bandwidth and c is the speed of light.

where

$$\check{\mathbf{x}}(t) = [x_1(t)\dots x_m(t)] \tag{2.4}$$

$$\check{\mathbf{n}}(t) = [n_1(t)\dots n_m(t)]. \tag{2.5}$$

$\mathbf{a}(\theta_i)$ is the antenna array response of signal impinging the array from θ_i, $\beta_i(t)$ is the complex gain of the i^{th} path. L defines the finite support of the channel and is dependent on choice of $g(t)$ and the path delays.

Assuming the receiver samples $\mathbf{x}(t)$ at times $t = kT_b \ \forall\ k \ \in Z$, we have the following discrete-time(DT) model:

$$\check{\mathbf{x}}(kT_b) = \sum_{i=0}^{\mathbf{I}} \mathbf{a}(\theta_i)\beta_i(kT_b)\mathbf{g}^T(0,\tau_i(kT_b))\mathbf{s}_k + \check{\mathbf{n}}(kT_b) \tag{2.6}$$

where

$$\mathbf{g}(t,\tau) = [g(t-\tau)\ g(t-T_b-\tau)\cdots g(t-(L-1)T_b-\tau)]^T \tag{2.7}$$

$$\mathbf{s}_k = [s_k\ s_{k-1}\cdots s_{k-L+1}]^T \tag{2.8}$$

From (2.6), and assume fading to remain constant over the symbol period, the oversampled multichannel data model can be expressed as

$$\mathbf{x}(kT_b) = \sum_{i=0}^{\mathbf{I}} \beta_i(kT_b)\left(\mathbf{a}(\theta_i)\otimes \mathbf{G}^T(\tau_i)\right)\mathbf{s}_k + \mathbf{n}(kT_b) \tag{2.9}$$

where

$$\mathbf{x}(kT_b) = \Big[x_1(kT_b)\cdots x_1((k+\frac{M-1}{M})T_b)\cdots \tag{2.10}$$

$$\cdots x_m(kT_b)\cdots x_m((k+\frac{M-1}{M})T_b)\Big]^T \tag{2.11}$$

$$\mathbf{G}(\tau) = \left[\mathbf{g}(0,\tau)\cdots\mathbf{g}(\frac{(M-1)T_b}{T_b},\tau)\right] \tag{2.12}$$

$$\mathbf{n}(kT_b) = \Big[n_1(kT_b)\cdots n_1((k+\frac{M-1}{M})T_b)\cdots \\ \cdots n_m(kT_b)\cdots n_m((k+\frac{M-1}{M})T_b)\Big]^T \tag{2.13}$$

and $M \in Z$ is the temporal oversampling factor. The operator $\otimes$ denotes the kronecker product.

Expressed in compact matrix form

$$\mathbf{x}(kT_b) = \mathbf{U}(\boldsymbol{\theta},\boldsymbol{\tau})\,(\boldsymbol{\beta}(kT_b)\otimes \mathbf{I}_L) + \mathbf{n}(kT_b) \tag{2.14}$$

where

$$\mathbf{U}(\boldsymbol{\theta},\boldsymbol{\tau}) = [\mathbf{u}(\theta_1,\tau_1)\cdots\mathbf{u}(\theta_I,\tau_I)] \tag{2.15}$$

$$\mathbf{u}(\theta_i,\tau_i) = \mathbf{a}(\theta_i)\otimes \mathbf{G}^T(\tau_i) \tag{2.16}$$

$$\boldsymbol{\beta}(t) = [\beta_1(t)\cdots\beta_I(t)]^T, \tag{2.17}$$

$\boldsymbol{\theta}= [\theta_1 \ \cdots \ \theta_I]^T$ and $\boldsymbol{\tau}= [\tau_1 \ \cdots \ \tau_I]^T$. In this thesis, we shall term $\mathbf{u}(\theta_i,\tau_i)$ as the **Block Space-Time Manifold.**

2.1.2 Continuous-Source Model

The model based on (2.2) is derived based on discrete sources. Alternatively, the combined effect of multipath, local scattering and diffraction can be seen as a continuum in time and space. Based on this assertion, the received signal in the CT domain can be expressed as

$$x(t) = \int_0^\infty a_{p\tau}(t)u(t-\tau)\exp(-j(\omega\tau+\theta_{p\tau}(t)))\mathrm{d}\tau. \tag{2.18}$$

The relationship between (2.18) and (2.2) can be easily established from [1]

$$a_{p\tau}(t)exp(-j(\omega\tau + \theta_{p\tau}(t))) = \sum_{\tau_i(t)=\tau} a_i(t)\exp(-j(\omega\tau + \theta_i(t))). \qquad (2.19)$$

Alternatively, we can write (2.18) as

$$\begin{aligned} x(t) &= c(t) \diamond g(t) \diamond \sum_i s_i \delta(t - iT_b) + n(t) && (2.20) \\ &= \sum_{i=0}^{L-1} h(t - iT_b)s_i + n(t) && (2.21) \end{aligned}$$

where $\diamond$ is the convolution operator, $h(t) = c(t) \diamond g(t)$ and

$$c(t) = \int_0^{\infty} a_{p\tau} \exp\left(-j(\omega\tau + \theta_{p\tau}(t))\right) d\tau. \qquad (2.22)$$

Sampling at times $t = kT_b$, we have

$$x(kT) = \mathrm{h}^T(0)\mathrm{s}_k + n(kT) \qquad (2.23)$$

where $\mathrm{h}(\Delta) = [h(\Delta)\ h(\Delta + Tb) \cdots h(\Delta + (L-1)T_b)]^T$ and Δ is the sampling phase. With temporal oversampling factor of M, we have

$$\check{\mathrm{x}}(kT_b) = \check{\Xi}\mathrm{s}_k + \check{\mathrm{n}}(t) \qquad (2.24)$$

with

$$\begin{aligned} \check{\mathrm{x}}(kT_b) &= \left[x(kT_b)\ x((k + \frac{1}{M})T_b) \cdots x((k + \frac{M-1}{M})T_b)\right] && (2.25) \\ \check{\Xi} &= \left[\mathrm{h}(0)\ \mathrm{h}(\frac{1}{M}T_b) \cdots \mathrm{h}(\frac{M-1}{M}T_b)\right]^T. && (2.26) \end{aligned}$$

The vectorized channel model in (2.24) leads to the same matrix form as derived by Tong *et.al.*. For multichannel receiving system, the channel model can be easily extended to

$$\mathrm{x}(kT_b) = \Xi\mathrm{s}_k + \mathbf{n}(kT_b) \qquad (2.27)$$

where

$$\Xi = \begin{bmatrix} \check{\Xi}_1 \\ \vdots \\ \check{\Xi}_n \end{bmatrix}. \tag{2.28}$$

Comparing (2.27) and 2.14),the equivalence is obvious.

Chapter 3

Parameter Estimation for Multipath Channel

In many wireless communication networks, the signals received by the base-station suffer impairments due to multipaths and additive noise. Under certain conditions, the multipath channels can be approximated and modelled parametrically by a finite number of path gains, direction of arrival (DOA) and time of arrival (TOA). Such parsimonious parametrization of the multipath channels can potentially offer improved accuracy gains in the estimation of the multipath channel. This can result in better sequence detection performance. Additionally, the estimated DOA and TOA can provide relevant information in the formulation of optimum transmit beamforming strategy as well as mobile localization.

Joint estimation of DOA and TOA of multipath signals can be achieved with *prior* knowledge of the array manifold and transmit-receive filter re-

sponse. The transmit-receive filter response can be easily obtained since the transmit and receive filter specifications can be enforced during manufacturing. In practice, the array manifold needs to be accurately calibrated. This can be achieved by applying array calibration algorithms such as [27][29][31][32].

In [10], van der Veen proposed to estimate the DOA and TOA directly from previously estimated channel parameter matrix using subspace fitting methods. This approach is later extended to space-time-polarization domain using vector sensor array processing[36]. These approaches however assume channel to remain stationary over the time-slot and require the channel to be estimated beforehand. In [37], Leshman and Wax assume the multipath to be fully coherent and propose a maximum likelihood approach that jointly estimates the DOA, TOA and path gains of multipath channels in the frequency domain. While this approach estimates the multipath parameters directly from the channel outputs (in frequency domain), it implicitly assumes the channel remained stationary over the observation period. The formulation in [37] can be cumbersome as it requires the DOA, TOA and path gains of the multipath channels to be estimated directly.

The main contribution of this chapter is the development of a new approach to estimate DOA and TOA of mulitpath channels. Unlike [10][37], the new approach does not assume channel stationarity over the time-slot nor does it require a start-up sequence in each time-slot to obtain estimates of the channel. The proposed approach accomplishes the estimation of DOA and TOA of multipath channels directly from an array of oversampled channel outputs. In this chapter, we derive the Cramer-Rao lower bound and formulate the maximum likelihood, weighted subspace fitting and MUSIC estimators.

In this development, we assume the data are transmitted in data packets over a time-division multiple access (TDMA) network. We also assume the DOA and TOA of the multipath channel remain constant over a small number of time-slots while the fading gains are time-varying within each time-slot. This assumption is reasonable when the base-station and fast moving mobiles are far from each other.

3.0.3 Data Model

The data model of the received channel outputs is given by

$$\mathrm{x}(kT_b) = \mathbf{U}(\boldsymbol{\theta}, \boldsymbol{\tau}) \left(\boldsymbol{\beta}(kT_b) \otimes \mathbf{I}_L\right) \mathrm{s}_k + \mathbf{n}(kT_b) \tag{3.1}$$

where

$$\begin{aligned}
\mathbf{U}(\boldsymbol{\theta}, \boldsymbol{\tau}) &= [\mathrm{u}(\theta_1, \tau_1) \cdots \mathrm{u}(\theta_I, \tau_I)] && (3.2)\\
\mathrm{u}(\theta_i, \tau_i) &= \mathrm{a}(\theta_i) \otimes \mathbf{G}^T(\tau_i) && (3.3)\\
\boldsymbol{\beta}(t) &= [\beta_1(t) \cdots \beta_I(t)]^T, && (3.4)\\
\boldsymbol{\theta} &= [\theta_1 \ \cdots \ \theta_I]^T && (3.5)\\
\boldsymbol{\tau} &= [\tau_1 \ \cdots \ \tau_I]^T && (3.6)
\end{aligned}$$

and $\otimes$ denotes the kronecker product operator. The parameter estimation can be formulated as follows:

Given N observations of the received vectors, estimate the parameter vector $\boldsymbol{\Psi}$

$$\boldsymbol{\Psi} = \left[\sigma^2 \ \boldsymbol{\eta}^T \ \mathrm{vec}^T(\mathrm{Re}(\mathbf{Z})) \ \mathrm{vec}^T(\mathrm{Im}(\mathbf{Z}))\right]^T. \tag{3.7}$$

where

$$\mathbf{Z} = [\mathbf{z}_1 \cdots \mathbf{z}_N] \quad (3.8)$$

$$\mathbf{z}_i = (\boldsymbol{\beta}(kT_b) \otimes \mathbf{I}_L)\, \mathbf{s}_k \quad (3.9)$$

and $\boldsymbol{\eta}^T = [\ \boldsymbol{\theta}^T \ \ \boldsymbol{\tau}]^T$.

3.1 Estimation Methods

Based on the model given in (3.1), the space-time covariance matrix is given as follows

$$\mathbf{R}(\boldsymbol{\eta}) = \mathbf{U}(\boldsymbol{\eta})\mathbf{P}\mathbf{U}^H(\boldsymbol{\eta}) + \sigma_w^2 \mathbf{I}_{mM} \quad (3.10)$$

where $\mathbf{P} = \mathrm{E}\left((\boldsymbol{\beta}(kT_b) \otimes \mathbf{I}_L)\mathbf{s}_t\mathbf{s}_t^H(\boldsymbol{\beta}(kT_b) \otimes \mathbf{I}_L)^H\right)$, σ_w^2 is the noise power and $\mathbf{A}^H$ denotes the conjugate transpose of $\mathbf{A}$. In this chapter, we assume the parametrization in (3.10) to be parameter identifiable. We also assume $nM > mL$ and $\mathbf{U}(\boldsymbol{\eta}, \boldsymbol{\tau})\mathbf{P}\mathbf{U}^H(\boldsymbol{\eta}, \boldsymbol{\tau})$ has rank $m'L$ where $m' \leq m$. From (3.1), we note that the multipath signals lie on the span of the block space-time manifold. Clearly from (3.10), we can apply many existing high resolution array processing algorithms to estimate $\boldsymbol{\theta}$ and $\boldsymbol{\tau}$.

The space-time covariance matrix can be estimated from N time slots of data packets of length J symbols by

$$\widehat{\mathrm{R}} = \frac{1}{NJ}[\mathrm{X}_1 \cdots \mathrm{X}_\mathrm{N}][\mathrm{X}_1 \cdots \mathrm{X}_\mathrm{N}]^H \quad (3.11)$$

where X_i, $i = 1 \cdots N$ is the data matrix constructed from the channel vectors of the i^{th} time-slot.

3.1.1 Maximum Likelihood Method

The ML estimation of $\boldsymbol{\eta}$ can be casted as follows:

$$\{\widehat{\boldsymbol{\eta}}, \mathbf{Z}\} = \arg\min_{\widehat{\boldsymbol{\eta}}, \mathbf{Z}} |\mathbf{X} - \mathbf{U}(\boldsymbol{\eta})\mathbf{Z}|_F^2 \ldots \tag{3.12}$$

Applying the technique of separation of variables [12], we have

$$\mathbf{Z}(\boldsymbol{\eta}) = \left(\mathbf{U}(\boldsymbol{\eta})^H \mathbf{U}(\boldsymbol{\eta})\right)^{-1} \mathbf{U}(\boldsymbol{\eta})^H \mathbf{X} \tag{3.13}$$

and the *concentrated* ML estimator of $\boldsymbol{\eta}$ is given by

$$\widehat{\boldsymbol{\eta}} = \arg\min_{\boldsymbol{\eta}} \operatorname{Tr}\left(\mathbf{P}^{\perp}_{\mathbf{U}(\boldsymbol{\eta})} \widehat{\mathbf{R}}\right) \tag{3.14}$$

where

$$\mathbf{P}^{\perp}_{\mathbf{U}(\boldsymbol{\eta})} = \mathbf{I} - \mathbf{U}(\boldsymbol{\eta}) \left(\mathbf{U}(\boldsymbol{\eta})^H \mathbf{U}(\boldsymbol{\eta})\right)^{-1} \mathbf{U}(\boldsymbol{\eta})^H \tag{3.15}$$

is the orthogonal projection matrix onto the subspace span by $\mathbf{U}(\boldsymbol{\eta})$, and

$$\widehat{\mathbf{R}} = \frac{1}{NJ} \mathbf{Z}\mathbf{Z}^H \tag{3.16}$$

is the sample space-time covariance matrix.

3.1.2 Subspace Fitting Method

The spectral decomposition of $\mathbf{R}(\boldsymbol{\eta})$ takes the form

$$\mathbf{R}(\boldsymbol{\eta}) = \mathbf{E}_s \boldsymbol{\Lambda}_s \mathbf{E}_s^H + \sigma_w^2 \mathbf{E}_n \mathbf{E}_n^H \tag{3.17}$$

$\boldsymbol{\Lambda}_s \in \mathbb{C}^{m'L \times m'L}$ is a diagonal matrix of signal eigenvalues. The range space of $\mathbf{E}_s \in \mathbb{C}^{nM \times m'L}$ and $\mathbf{E}_n \in \mathbb{C}^{nM \times (nM - m'L)}$ are the signal and noise subspaces, respectively. Since $\mathbf{U}(\boldsymbol{\eta})$ is full column rank and (3.10) is assumed to be parameter identifiable, we have the following relationships

$$\left|\mathbf{E}_n^H \mathbf{U}(\boldsymbol{\eta}^{'})\right|_F = 0 \text{ and } \mathbf{E}_s = \mathbf{U}(\boldsymbol{\eta}^{'})\mathbf{T} \tag{3.18}$$

if and only if $\boldsymbol{\eta}^{'} = \boldsymbol{\eta}$. $\mathbf{T} \in \mathbb{C}^{m^{'}L \times m^{'}L}$ is an unitary matrix. Many subspace based algorithms can be applied directly here to the solution of (3.18)[15].

Multiple Signal Classification Algorithm

Multiple Signal Classification Algorithm (MUSIC) is one of the most popular array processing algorithm developed for direction finding[13]. Following (3.18) and with $\mathbf{P}$ being full-rank, the directions and times of arrival, $\{\theta_i, \tau_i\}$ of the multipath signal can be obtained from the MUSIC DOA-TOA cost function

$$f_{MUSIC}(\theta, \tau) = \frac{\|\mathbf{u}(\theta,\tau)\|}{\|\mathbf{E}_n^H \mathbf{u}(\theta,\tau)\|}. \tag{3.19}$$

Unlike conventional MUSIC algorithm, the space-time manifold, $\mathbf{u}(\theta,\tau)$, is not described by a vector. As defined in (2.17). $\mathbf{u}(\theta,\tau)$ describes the space and time variation of the oversampled array response of a known signal, $g(t-\tau)$, impinging the antenna array from θ.

Weighted Subspace Fitting

From the relationships of (3.18), the directions and times of arrival can be estimated by optimizing the following measure

$$\hat{\boldsymbol{\eta}} = \arg\min_{\boldsymbol{\eta}} \|\mathbf{E}_s - \mathbf{U}(\boldsymbol{\eta})\mathbf{U}(\boldsymbol{\eta})^{\dagger}\mathbf{E}_s\|_{\mathbf{W}}^2 \tag{3.20}$$

$$= \arg\min_{\boldsymbol{\eta}} \operatorname{Tr}\left(\mathbf{P}_{\mathbf{U}(\boldsymbol{\eta})}^{\perp} \hat{\mathbf{E}}_s \mathbf{W} \hat{\mathbf{E}}_s^H\right) \tag{3.21}$$

where $\|\mathbf{A}\|_{\mathrm{Q}} = \mathrm{Tr}(\mathbf{AQA}^H)$ and $\mathbf{A}^\dagger$ denotes pseudo-inverse of $\mathbf{A}$; $\mathbf{W} \in \mathbb{C}^{m'L \times m'L}$ is a positive definite weighting matrix. The cost function in (3.21) is known as Weighted Subspace Fitting (WSF). The results in [14] suggest an appropriate choice of $\mathbf{W}$ to be

$$\mathbf{W} = \left(\widehat{\mathbf{\Lambda}}_s - \widehat{\sigma^2}\mathbf{I}\right)^2 \widehat{\mathbf{\Lambda}}_s^{-1} \tag{3.22}$$

where $\widehat{\mathbf{\Lambda}}_s$ and $\widehat{\sigma^2}\mathbf{I}$ are, respectively, the eigenvalues associated with the signal and noise eigenvectors.

3.2 Numerical Examples

Computer simulations were conducted to evaluate the ability to estimate the DOA and TOA of multipath signals by the proposed algorithms. We consider a six-element antenna array with four times temporal oversampling of the symbol rate. The carrier frequency used is 1800MHz. The data symbols are drawn from binary phase shift keying constellation and transmitted in packets of 150 symbols at GSM data rate. The modulation waveform is a raised cosine pulse with 35% roll-off. The multipath channel is parametrized by paths arriving from $\theta_1 = 20^\circ$ and $\theta_2 = 30^\circ$ with corresponding path delays of $\tau_1 = 2\mu$sec and $\tau_2 = 3\mu$sec. In this study, the effective channel length is approximately $6T_b$. The fast time-varying fading amplitudes are due to the mobile travelling at 300kph (doppler frequency of 500Hz) and assumed to be Rayleigh distributed. For each trial, we compute the sample space-time covariance matrix from 40 time-slots and the fading amplitudes are independently generated for each time-slot. The statistics computed in this study are averaged directly from 100 independent trials.

In Figure 3.1, we examine the performance of the proposed algorithms over a range of SNR. As expected, the ML and the WSF method outperform the MUSIC estimator. Next, we study the effects of mobile speed on the proposed algorithms. In Figure 3.2, the MSE of the estimated DOA and TOA are plotted as a function of mobile speed. We note that in this experimental setup, the speed of the mobile has little impact on the performance. It suffices to note that when the mobile is travelling at very high speed, the assumption of DOA-TOA invariance can only hold for a short period of time. We examine the performance of the proposed estimators as a function of the number of snapshots in Figure 3.3. The results show that the ML and WSF estimator achieve good performance with short integration time.

3.3 Conclusions

This chapter considers the parameter estimation problem for directions and times of arrival of multipath signals in mobile communications environment. This is an important problem in mobile communications particularly for mobile localization services, survellience and in the formulation of optimum transmit beamforming.

Starting from the continuous-time domain, we model the space-time multipath channel as a collection of basis functions. These basis functions lie on a *block space-time manifold.* The significance of this formulation is that the resulting mathematical structure is very similar to the ones used in high resolution direction finding algorithms, thereby enabling many previously

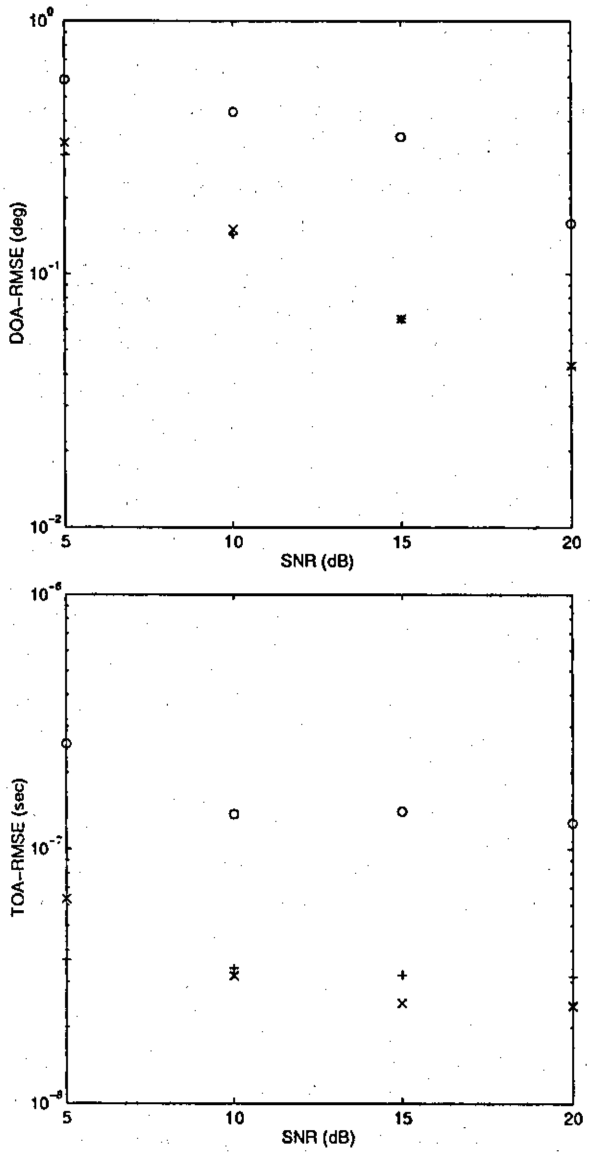

Figure 3.1: MSE versus SNR. ×: ML, +: WSF, o: MUSIC. Mobile Speed: 83.3metres/sec . Number of Symbol Per Time-slot: 150

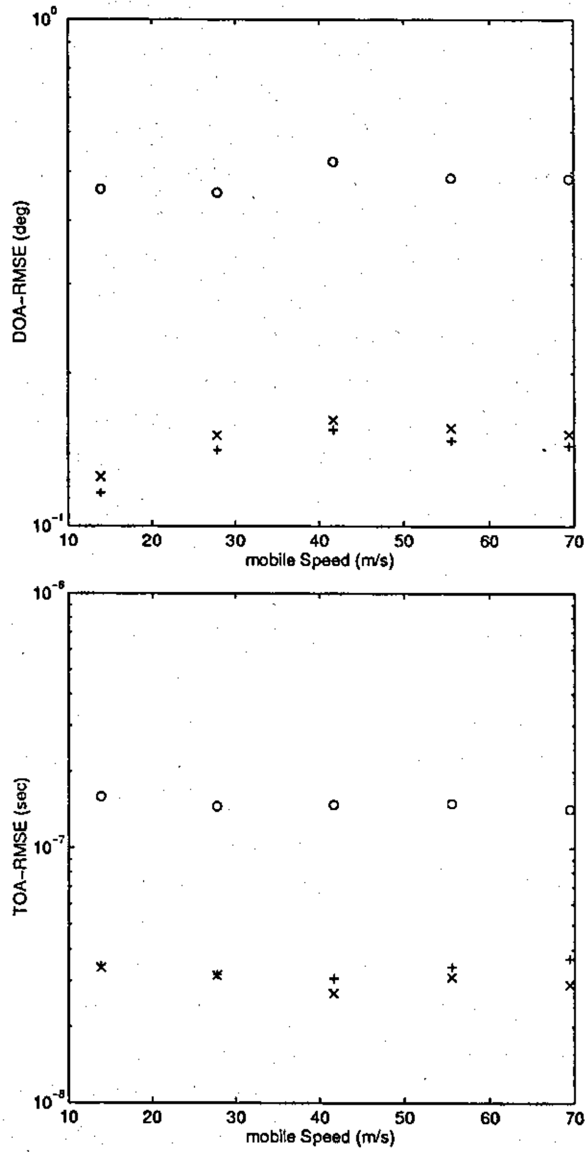

Figure 3.2: MSE versus Mobile Speed. $\times$: ML, $+$: WSF, $\circ$: MUSIC. SNR: 10dB. Number of Symbol Per Time-slot: 150

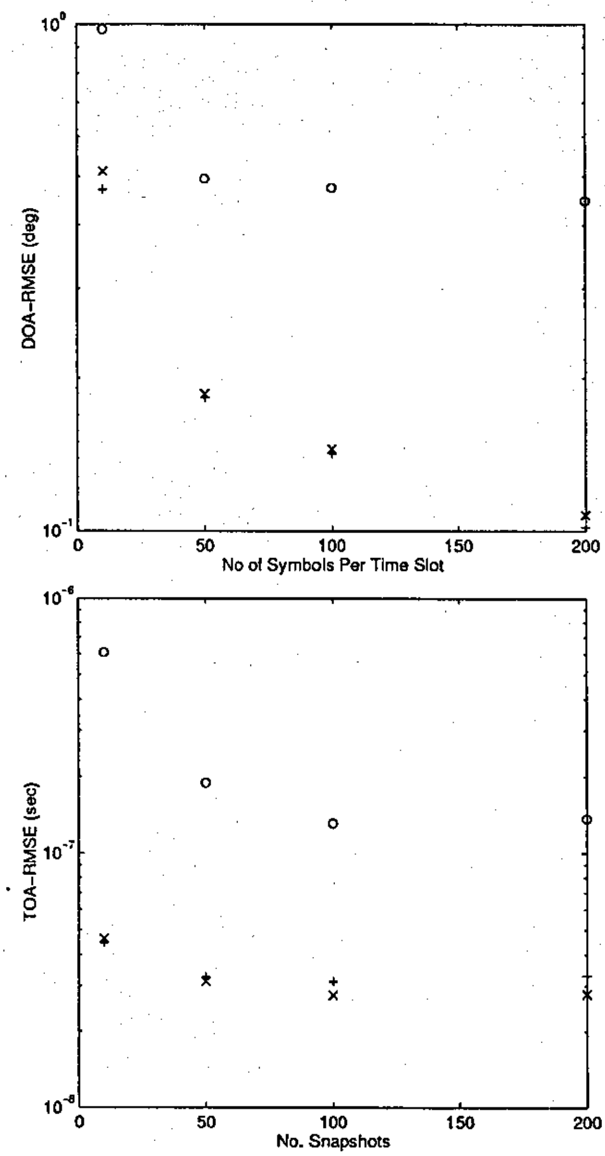

Figure 3.3: MSE versus Number of Symbols Per Time-Slot. ×: ML, +: WSF. o: MUSIC. Mobile Speed: 83.3metres/sec SNR: 10dB.

developed array processing algorithms to be applied here with minimal modification. We present a maximum likelihood estimator and derived subspace fitting algorithms such as weighted subspace fitting and MUSIC estimators to estimate the multipath directions and times of arrival. The MUSIC estimator offers significant computational simplicity over the WSF and ML estimators but compromises in estimation performance. The usefulness of the proposed approach is demonstrated with numerical examples.

Chapter 4

Adaptive Algorithms for Channels with ISI Impairments

4.1 Introduction

The main technical challenges and requirements of developing channel identification and equalization algorithms for wireless mobile time-division multiple access (TDMA) networks using short burst data formats can be succinctly summarized as follows:

1. Ability to track time-varying channels.

2. Require an extremely short or no training sequence for initial channel estimation.

3. Data efficient and rapidly convergent for use with short burst data format.

4. Perform adequately at relatively low signal to noise ratio (SNR).

Several families of blind channel identification and equalization algorithms have been proposed. However, many of the current approaches may not be adequate for such mobile communications applications. For instance, algorithms based on exploiting higher order statistical information in the channel outputs [18] [19] find limited applications in wireless mobile communications. This is because these algorithms generally exhibit slow convergence and require a large number of channel outputs to obtain good estimates of the higher order statistics for reliable channel equalization.

The pioneering works of Tong *et. al.* [22] and Moulines *et. al* [23] have led to the developments of several blind channel identification algorithms based on the second-order cyclostationary properties of the channel outputs. In general, these methods achieve blind channel equalization by solving a system of linear equations derived from the covariance matrix of the vectorized channel outputs. These algorithms are block-based and offer the potential of fast and data efficient blind channel identification. However, their explicit assumption of channel stationarity renders them unsuitable for radio propagation channels that are rapidly time-varying[1].

---

[1]These algorithms can still find useful applications in fast time-varying channels when the data packet is very short such that the time-variation within the time-slot can be approximated to be stationary

A conventional adaptive channel equalizer treats the acquisition and tracking problem separately whereby tracking and equalization will commence when the tracking algorithm has achieved steady state. The drawback of this approach is that the training sequence will have to be sufficiently long to ensure the channel estimator reaches its steady state before the channel is tracked and equalized realiably. When short training sequence can only be made available due to bandwidth conservation, the detected symbols at the start of the equalization process will have higher probability of error due to the noisier channel estimates.

In most digital communication systems, the transmitted symbols are constrained to a finite alphabet (FA) set $\mathbf{\Omega}$. This will in turn limit the noiseless channel outputs to a finite set. The trellis relationship of channel outputs is determined by the state transitions of the transmitted data and the multipath propagation channel. This trellis relationship not only provides a useful constraint. it also shows that channel identification and equalization of unknown channels can be achieved optimally (in least-squares sense) by joint channel estimation and sequence detection. In practice, joint channel estimation and sequence detection is difficult to implement and suboptimal solutions have been proposed. For example, Seshadri [20] proposed a fast blind trellis search algorithm based on Generalized Viterbi Algorithm (GVA) where data detection and channel estimation are performed recursively but separately. If GVA is applied directly, a preamble is required in the time-slot for the channel estimator to acquire the channel parameters and reach steady state before reliable tracking and equalization can commence. Similar to the conventional adaptive channel equalization techniques, a short preamble can lead to poor sequence detection performance due to noisy channel estimates.

In this chapter, we consider the problem of semi-blind identification and equalization of time-varying channels where only a short training sequence is available. We recognize that the finite-alphabet properties of the data sequence offer additional information to the estimation of the channel parameters. By exploiting this information together with the richness of the inherent structural relationship between channel parameters, data sequence and channel ouputs, better channel identification and sequence detection performance can be expected. We use a forward-backward optimization procedure to exploit the said structural information and constraints of the received signals. In the following sections, we describe the data model and propose algorithms, present simulation results and analyse their computational complexity.

4.2 Data Model and Problem Formulation

Consider an m elements antenna array where each array channel output is oversampled by M times the symbol period T_b. The channel output vector can be compactly written as [22]

$$\mathrm{x}(kT_b) = \Xi(kT_b)\mathrm{s}_k + \mathrm{n}(kT_b) \tag{4.1}$$

where

$$\begin{aligned} \mathrm{x}(kT_b) &= \Big[x_1(kT_b)\ldots x_1((k+\frac{M-1}{M})T_b)\ldots \\ &\quad \ldots x_m(kT_b)\ldots x_m((k+\frac{M-1}{M})T_b)\Big]^T \\ \mathrm{n}(kT_b) &= \Big[n_1(kT_b)\ldots n_1((k+\frac{M-1}{M})T_b)\ldots \end{aligned} \tag{4.2}$$

$$\ldots n_m(kT_b)\ldots n_m((k+\frac{M-1}{M})T_b)\Big]^T. \quad (4.3)$$

$x_i(kT_b)$ and $n_i(kT_b)$ are the channel output and observation noise of the i^{th} array channel at time kT_b. $s_k \in \Omega$ is the transmitted symbol at kT_b and LT_b is the effective length of the time varying channel impulse response $\Xi(kT_b)$. The symbol vector is given by

$$\mathrm{s}_k = [s_k \ldots s_{k-L+1}]^T. \quad (4.4)$$

Suppose the noise $\mathrm{n}(kT_b)$ is a zero-mean Gaussian random process and P number of channel output vectors are received, the least squares estimation of the channel parameter and detection of the data sequence can be obtained by solving the mixed continuous-FA parameter optimization problem:

$$\left\{\{\hat{\Xi}(kT_b)\}_{k=1}^{P}, \hat{\mathrm{S}}\right\} = \arg\min \sum_{k=1}^{P} |\mathrm{x}(kT_b) - \Xi(kT_b)\mathrm{s}_k|_F^2. \quad (4.5)$$

$\{\Xi(kT_b)\}_{k=1}^{P}$ are the continuous parameter and $\mathrm{S} = [\mathrm{s}_1, \ldots, \mathrm{s}_P]$ is a Toeplitz matrix parametrized by

$$\tilde{\mathrm{s}} = [s_{-L}, \ldots, s_P]^T. \quad (4.6)$$

The elements in S are constrained to the FA set Ω.

We write an equivalent time-reversed version of (4.5) as

$$\left\{\{\hat{\Xi}_r(kT_b)\}_{k=1}^{P}, \hat{\mathrm{S}}_r\right\} = \arg\min \sum_{k=1}^{P} |\mathrm{x}_r(kT_b) - \Xi_r(kT_b)\mathrm{s}_{rk}|_F^2 \quad (4.7)$$

where $\mathrm{x}_r(kT_b) = \mathrm{x}(lT_b)$ and $\mathrm{s}_{rk} = [s_{l-L+1}, \ldots, s_l]^T$. The time-reversed channel matrix $\Xi_r(kT_b)$ is constructed by "flipping over" the rows of $\Xi(lT_b)$. They are related by

$$[\Xi_r(kT_b)]_{i,k} = [\Xi(lT_b)]_{i,L-k+1} \quad (4.8)$$

and $l = P - k + 1$. $[\mathbf{A}]_{i,j}$ denotes the matrix element located at the i^{th} row and j^{th} column of $\mathbf{A}$. Similarly, the symbol matrix

$$\mathbf{S}_r = [\mathbf{s}_{r1} \ldots \mathbf{s}_{rP}] \tag{4.9}$$

is a Toeplitz matrix parametrized by

$$\tilde{\mathbf{s}}_r = [s_P \ldots s_{-L}]^T. \tag{4.10}$$

Under the ideal conditions of perfect initial estimates and perfect tracking, the adaptive Maximum Likelihood Sequence Detection (MLSD) algorithms such as [20] [21] can achieve optimal channel identification and equalization. However, in practical radio environment where short burst data formats are used and multipath propagation channels are time-varying, the following issues need to be addressed:

1. Good initial estimates of the channel are spectrally expensive to achieve as this entails reserving portion of the data sequence for non-blind channel estimation. Due to the presence of noise, reducing the training length will result in noisier initial estimates and induce errors in the sequence detection.

2. When $\Xi(kT_b) = \Xi(iT_b)$ for all $\{i, k\}$ is imposed on time-varying channels, modelling errors will appear resulting in poorer sequence detection. One can argue that the time-varying channel be approximated by contiguous segments of time-invariant channel where each data sub-block is independently processed. This is suboptimal as the full information residing within the data block is not exploited. Moreover,

resolving the competing requirements of large sub-block size and containing modelling errors remain open.

3. Joint estimation of time-varying channels and sequence detection is difficult to implement. Suboptimal approaches that estimate the channel parameters and perform data detection recursively but *separately* have been proposed [20] [21]. In general, the decoupled optimization of the least squares (LS) cost function will lead to a suboptimal solution.

4.3 Adaptive Algorithms for Least-Squares Space-Time Channel Identification and Equalization

In this section, we extend from our previous work [43][2] and propose an approach that can potentially resolve the mentioned issues by processing the received data in batch mode and optimizing the LS cost function iteratively in a forward-backward manner.

Herein the proposed approach begins with a noisy (but of *sufficient* accuracy to avoid divergence) initial channel estimate. Then it seeks to optimize the LS cost function alternately and recursively with respect to the channel parameters and data sequence. Towards the end of the forward iteration, the

[2] The forward-backward optimization in [43] is used to alleviate the need for known symbol sequence to initialize the Viterbi algorithm. A similar optimization procedure was reported in [55] to improve the data efficiency of modulus restoral based blind equalization algorithms.

corresponding channel parameters are likely to converge nearer the true estimates, and the symbol vectors will have a lower probability of error. However the symbol vectors at the start of the data packet will have higher probability of error due to the poorer channel estimation and tracking. The local minima of (4.5) is not likely to be attained due to a combination of errors from channel estimation, tracking and sequence detection as well as suboptimal optimization of (4.5). In the backward iteration, (4.7) (the time reversed version of (4.5)) is similarly minimized based on the initial state extracted from the last symbol vector in **S** and its corresponding time-reversed channel estimates. The improved initial estimates can lead to more accurate estimation of S and $\{\Xi(kT_b)\}_{k=1}^{P}$. Hence, with each forward-backward optimization iteration, the residual in (4.5) will be further reduced with the improved estimates of **S** and $\{\Xi(kT_b)\}_{k=1}^{P}$. The cyclic refinement of the channel estimates and sequence detection will monotonically decrease the LS cost function and finally converge to local minimum.

The decoupled channel estimation and sequence detection process are executed recursively but separately in the following manner. The symbol vector at time kT_b is decided based on the last updated channel estimates. The channel estimates are then adaptively updated in a decision directed manner based on the *latest* detected symbol vectors. In traditional adaptive MLSD [56], decision delay is necessary in Viterbi algorithm and decision feedback equalizer to achieve reliable sequence or symbol detection for decision directed channel update. It is important to note that such inherent delay will degrade the estimation and tracking of fast time varying channel.

Next, we present two algorithms for estimating the channel parameters matrix and detecting the data sequence based on the mentioned approach.

Algorithm I

One way to exploit the inherent Toeplitz structure of the symbol matrix $\mathbf{S}$ recursively is by applying the Viterbi algorithm (VA). The cost function in (4.5) can be rewritten as

$$\Lambda\left(\mathbf{a}_P^l\right) = \sum_{k=1}^{P} \left|\mathbf{x}(kT_b) - \Xi(kT_b)\mathbf{s}_k^l\right|_F^2 \tag{4.11}$$

where

$$\mathbf{a}_P^l = \left[s_{-L}^l \dots s_P^l\right]^T \tag{4.12}$$

is the l^{th} possible symbol sequence. In the ideal conditions of noiseless channel and with perfect channel knowledge, we have

$$l_{opt} = \arg\min_l \Lambda\left(\mathbf{a}_P^l\right) \tag{4.13}$$

such that

$$\mathbf{a}_P^{l_{opt}} = \hat{\mathbf{s}}. \tag{4.14}$$

We can write the accumulated metric of (4.11) at time k recursively as

$$\Lambda\left(\mathbf{a}_k^l\right) = \Lambda\left(\mathbf{a}_{k-1}^l\right) + \left|\mathbf{x}(kT_b) - \Xi(kT_b)\mathbf{s}_k^l\right|_F^2 \tag{4.15}$$

where the symbol vectors, $\mathbf{s}_k^l$ and $\mathbf{s}_{k-1}^l$, are related by

$$\begin{aligned} \mathbf{s}_k^l &= \left[s_k^l \ \dots \ s_{k-L+1}^l\right]^T \\ \mathbf{s}_{k-1}^l &= \left[s_{k-1}^l \ \dots \ s_{k-L}^l\right]^T; \end{aligned} \tag{4.16}$$

hence imposing the Toeplitz structure on the detected symbol matrix. The Viterbi algorithm (VA) uses the recursion relation of (4.15) and solves (4.5) efficiently based on the notion that the globally best path l_{opt} must also be locally best as the symbol vectors (states) transverse from $k = 1$ to $k = P$.

The VA is applied assuming perfect knowledge of the channel parameter matrix which is not the case as the channel parameters in the problem considered herein are time-varying. In addition, the channel parameters are likely to be noisy if they are estimated from a short training sequence. To track the variation of the channel parameters, they need to be updated separately at each time kT_b based on the tentative decisions of s_k^l. In [20], Seshadri asserts that such tentative decisions may not be reliable initially, therefore the paths entering each state should not be discarded. He suggests a Generalized Viterbi algorithm (GVA) that retains a number of "locally best" survivors entering each state and updates the channel estimates associated with each survivor independently. A simplified version of GVA was reported in [21] where only one locally best survivior entering each state is retained.

The computational complexity of employing GVA in the proposed approach can become prohibitive. In this development, we adopt a simpler adaptive VA implementation. We propose that only one survivor associated with the p^{th} state at time k, $\mathrm{s}_k(p) \in \Omega^{L+1}$, is retained

$$l_k^p = \arg\min_{l \in \Theta_k^p} \Lambda\left(\mathrm{a}_{k-1}^l\right) + \left|\mathrm{x}(kT_b) - \widehat{\Xi}^l(kT_b)\mathrm{s}_k(p)\right|_F^2 \qquad (4.17)$$

where Θ_k^p denotes the indices of the paths entering state $\mathrm{s}_k(p)$ and $\widehat{\Xi}^l(kT_b)$ is the estimated channel parameter matrix associated with the l^{th} path. To reduce the storage and computational load further, we use a common channel parameters matrix for metric computation. It is adaptively updated based on the survivor with the lowest accumulated metric by the computationally efficient Least Mean Squares (LMS) algorithm [65]

$$\left[\widehat{\Xi}(kT_b))\right]_{i\cdot} = \left[\widehat{\Xi}((k-1)T_b)\right]_{i\cdot} + \mu \widehat{\mathrm{s}}_k^{\kappa T} \left([\mathrm{x}(kT_b)]_i - \left[\widehat{\Xi}(kT_b))\right]_{i\cdot} \widehat{\mathrm{s}}_k^{\kappa} \right). \quad (4.18)$$

Expressed (4.18) compactly in matrix form, we have

$$\widehat{\Xi}(kT_b) = \widehat{\Xi}((k-1)T_b) + \mu \left(\mathbf{1}_{mM} \otimes \widehat{\mathrm{s}}_k^{\kappa T} \right) \odot \left(\boldsymbol{\eta}(kT_b) \otimes \mathbf{1}_L^T \right) \quad (4.19)$$

where

$$\boldsymbol{\eta}(kT_b) = \mathrm{x}(t) - \widehat{\Xi}((k-1)T_b)\widehat{\mathrm{s}}_k. \quad (4.20)$$

$\widehat{\mathrm{s}}_k$ is the tentative estimate of the k^{th} symbol vector of path with the lowest accumulated metric at time k is defined by

$$\kappa = \arg\min_p \ l_k^p. \quad (4.21)$$

The symbol $\mathbf{1}_K$ is a K-dimensional vector of 1 and μ is the adaptation step-size. $\otimes$ and $\odot$ are the Kronecker and Hadamard matrix products, respectively. The time-reversed version of (4.19) can be similarly derived.

The algorithm proposed herein is summarized as follows.

- Compute the initial estimates of $\Xi(T_b)^{(0)}$ and derive the initial state $\mathrm{s}^{(l)}(0)$ from the start-up sequence. Set $l = 0$.
- Repeat
  - Optimize (4.5) by joint channel matrix estimation using (4.19) and sequence detection using VA.

- Perform Time-reversal to obtain $\{\hat{\Xi}_r(kT_b)^{(l)}\}_{k=1}^{P}$ and $\hat{\mathbf{S}}_r^{(l)}$ from $\{\hat{\Xi}(kT_b)^{(l)}\}_{k=1}^{P}$ and $\hat{\mathbf{S}}^{(l)}$, respectively.

- Set

$$\mathbf{s}_r^{(l)}(0) = \begin{bmatrix} [\mathbf{S}_r^{(l)}]_{2\cdots L,1} \\ \kappa \end{bmatrix} \tag{4.22}$$

  where $[\mathbf{A}]_{i\cdots k,l}$ denotes a vector consisting of the i^{th} to k^{th} row elements in the l^{th} column of the matrix $\mathbf{A}$ and κ is any element in FA set.

- Optimize (4.7) by joint channel matrix estimation using the time-reversed version of (4.19) and sequence detection by VA.

- Perform time-reversal to obtain $\{\hat{\Xi}(kT_b)^{(l)}\}_{k=1}^{P}$ and $\hat{\mathbf{S}}^{(l)}$ from $\{\hat{\Xi}_r(kT_b)^{(l)}\}_{k=1}^{P}$ and $\hat{\mathbf{S}}_r^{(l)}$, respectively.

- Set $l = l + 1$

• Repeat until convergence, if possible.

Algorithm II

To reduce the computational load and memory requirements further, we replace the VA-based sequence detector with a symbol by symbol detection approach that partially exploits the Toeplitz structure of $\mathbf{S}$ [43] [44]. We can write the spatio-temporal channel output vectors observed through a temporal window of order v as

$$\mathbf{y}(kT_b) = \mathbf{C}\,(\Xi(kT_b))\,\mathbf{q}_k + \mathbf{w}(kT_b) \tag{4.23}$$

where

$$
\begin{aligned}
\mathbf{y}(kT_b) &= \left[\mathbf{x}(kT_b)^T \cdots \mathbf{x}((k-v+1)T_b)^T\right]^T && (4.24)\\
\mathbf{w}(kT_b) &= \left[\mathbf{n}(kT_b)^T \cdots \mathbf{n}((k-v+1)T_b)^T\right]^T && (4.25)\\
\mathbf{q}_k &= \left[s_k \ldots s_{k-L-v+2}\right]^T && (4.26)
\end{aligned}
$$

and $\mathbf{C}(\mathbf{A})$ is a block Toeplitz matrix of $\mathbf{A}$. It suffices to note that (4.23) assumes the variations of channel parameters in the temporal window to be insignificant. This is a reasonable assumption even in rapidly time-varying channels if the selected v is not too large.

The least-squares estimation of the channel parameters and data sequence becomes

$$
\left\{\{\widehat{\Xi}(kT_b)\}_{k=1}^{P}, \widehat{\mathbf{Q}}\right\} = \min \sum_{k=1}^{P} |\mathbf{y}(kT_b) - \mathbf{C}(\Xi(kT_b))\mathbf{q}_k|_F^2 \qquad (4.27)
$$

where $\mathbf{Q}$ is the Toeplitz symbol matrix

$$
\mathbf{Q} = \begin{bmatrix} s_1 & s_2 & \cdots & s_P \\ s_0 & s_1 & \cdots & \vdots \\ \vdots & \vdots & \cdots & \vdots \\ s_{-L-v+2} & \cdots & \cdots & s_{P-L-v+2} \end{bmatrix}. \qquad (4.28)
$$

Similarly, the time-reversed version of (4.27) is given by

$$
\left\{\{\widehat{\Xi}_r(kT_b)\}_{k=1}^{P}, \widehat{\mathbf{Q}}_r\right\} = \min \sum_{k=1}^{P} |\mathbf{y}_r(kT_b) - \mathbf{C}(\Xi_r(kT_b))\mathbf{q}_{rk}|_F^2 \qquad (4.29)
$$

where

$$
\begin{aligned}
\mathbf{y}_r(kT_b) &= [\mathbf{x}((l-v+1)T_b)^T \cdots \mathbf{x}(lT_b)^T]^T && (4.30)\\
\mathbf{q}_{rk} &= [s_{l-L-v+2} \ldots s_l]^T && (4.31)
\end{aligned}
$$

and $l = P - k + 1$.

The symbol-by-symbol detection can be conducted in the following manner. Given the tentative detection of the k^{th} symbol vector

$$\hat{\mathrm{q}}_k = [\hat{s}_k \cdots \hat{s}_{k-L-v+2}]^T \tag{4.32}$$

and estimated channel matrix $\hat{\Xi}(kT_b)$, the tentative detection of the $(k+1)^{th}$ symbol vector is given by

$$\hat{q}_{k+1} = \begin{bmatrix} \hat{\phi}_f \\ \hat{\phi}_{fb} \end{bmatrix} \tag{4.33}$$

where

$$\hat{\phi}_f = \min_{\phi_f \in \Omega^{n_{ff}}} \left\| \mathrm{y}((k+1)T_b - \mathbf{C}(\hat{\Xi}(kT_b)) \begin{bmatrix} \hat{\phi}_f \\ \hat{\phi}_{fb} \end{bmatrix} \right\|_F^2 \tag{4.34}$$

and

$$\hat{\phi}_{fb} = [\hat{s}_k]_{k-n_{ff}+1\cdots k-L-v+3,1}. \tag{4.35}$$

The LMS channel parameters matrix update is computed as follows:

$$\boldsymbol{\xi}_k = \boldsymbol{\xi}_{k-1} + \mu \left(\hat{\mathrm{q}}_k^T \otimes \mathbf{I}_{vmM} \boldsymbol{\Gamma} \right)^H \left(\mathrm{y}(kT_b) - \mathbf{C}\left(\Xi((k-1)T_b) \right) \hat{\mathrm{q}}_k \right) \tag{4.36}$$

where

$$\boldsymbol{\xi}_k = \mathrm{vec}(\hat{\Xi}(kT_b)) \tag{4.37}$$

and vec($\mathbf{A}$) stacks the column vectors of $\mathbf{A}$ into a single column vector. The matrix $\boldsymbol{\Gamma}$ is a selection matrix such that $\boldsymbol{\Gamma}\mathrm{vec}(\mathbf{A}) = \mathrm{vec}(\mathbf{C}(\mathbf{A}))$.

The algorithm based on symbol-by-symbol detection approach of (4.34) is summarized as follows:

Given a start-up sequence, compute the initial estimates of $\Xi(T_b)^{(0)}$ and derive the initial state $\mathrm{q}^{(l)}(0)$. Set $l = 0$.

1. For $k = 1 \cdots P$, optimize (4.5) by joint symbol vector detection and channel matrix estimation using (4.34) and (4.19), respectively.

2. Perform time-reversal to obtain $\{\widehat{\Xi}(kT_b)_r^{(l)}\}_{k=1}^{P}$ and $\widehat{\mathbf{Q}}_r^{(l)}$ from $\{\widehat{\Xi}(kT_b)^{(l)}\}_{k=1}^{P}$ and $\widehat{\mathbf{Q}}^{(l)}$, respectively.

3. Set

$$\mathbf{q}_r^{(l)}(0) = \left[[\mathbf{Q}_r^{(l)}]_{2\cdots L,1}^T \ \kappa\right]^T \tag{4.38}$$

where κ is any element in $\mathbf{\Omega}$.

4. For $k = 1 \cdots P$, optimize (4.7) by joint symbol vector detection and channel matrix estimation using (4.34) and (4.36), respectively.

5. Perform time-reversal to obtain $\{\widehat{\Xi}(kT_b)^{(l)}\}_{k=1}^{P}$ and $\widehat{\mathbf{Q}}^{(l)}$ from $\{\widehat{\Xi}_r(kT_b)^{(l)}\}_{k=1}^{P}$ and $\widehat{\mathbf{Q}}_r^{(l)}$, respectively.

6. Set $l = l + 1$

7. Repeat (1)-(6) until convergence, if possible.

8. Choose $\widehat{\mathbf{Q}}^{(l)}$ or $\widehat{\mathbf{Q}}_r^{(l)}$ based on their corresponding residuals and force it to be Toeplitz based on majority rule.

4.4 Simulation Results

In this section, we describe some simulation results from the proposed algorithms. We consider a two element antenna array with temporal oversampling 2 times the symbol rate. The carrier frequency used is 900MHz. The data symbols are drawn from $\Omega \exists \{-1, 1\}$ and transmitted at GSM data rate of 277kps in packets of 100 symbols each. The combined transmit and receive filter frequency response is a raised cosine with roll-off factor of 35%. We simulate the Rayleigh multipath environment based on the TU channel from the ETSI recommendations[24] with paths arriving with a uniform spatial distribution. The local spread of each path is 30 degrees. In this study, we restrict the channel length to $L = 3$ and fix $v = 3$ and $n_{ff} = 3$.

Figure 4.1 shows the bit error rates for the proposed Algorithms I and II and GVA as a function of SNR. The step-sizes used for LMS channel update in Algorithm I and II are 0.0025 and 0.01, respectively. The initial channel estimates are obtained from an extremely short training sequence of 5 symbols using direct matrix inversion. Herein, the GVA retains $K = 4$ locally best survivors entering each state. The results are averaged directly from 5000 independent trials. The relative speed between the transmitter and receiver is 300km/hr. This will induce in a doppler frequency of 250Hz. It is interesting to note that both Algorithm I and II have similar BER performance. But it suffices to note that Algorithm II has a relatively smaller computational and memory requirement. We also note that at error rate of 10^{-3}. the proposed algorithms suffer a loss of 3dB against the known channel bound. On the other hand, GVA suffers 9dB. In other words, the proposed algorithms achieve a 6dB gain over GVA in this numerical example.

Figure 4.2 compares the proposed algorithms against GVA with estimated and exact initial channel estimates. It is important to highlight that the BER performance of the proposed algorithm is obtained from noisy initial channel parameters estimated with training sequence of 5 symbols. We note in

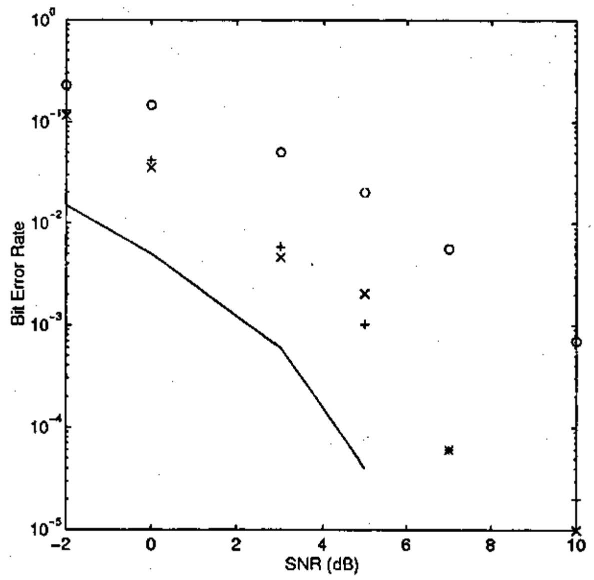

Figure 4.1: BER versus SNR. ×: Algorithm I, +: Algorithm II, o:GVA, -: Known Channel Bound

Figure 4.2 that even with exact initial channel estimates, GVA has BER floors around 10^{-4}. Such flooring is likely to result from tracking errors. The proposed algorithms do not seem to exhibit error flooring upto SNR of 10dB. In fact, the proposed algorithms achieve one order magnitude BER performance improvement over GVA. This suggests We observe that the BER performance curve of the proposed algorithms and GVA with exact initial estimates crosses at 5dB. This is likely due to the fact that the sequence detection errors are mainly contributed by the channel noise and the noisier initial channel estimates. But when SNR> 5dB, tracking errors become the dorminant source of error. The performance loss at SNR< 5dB is however less than 3dB. The results signify the importance of channel estimators that are highly robust to high level of noise. One way to achieve this is to parameterize the channel parsimoniously. For example, using the knowledge of the transmit and receive filter response, the "structured" channel parameter matrix can be formulated. Such approach was first reported in [57] and later in [63] and [64].

Figure 4.3 plots the BER performance of the proposed algorithms as a function of doppler frequency at signal to noise ratio of $7dB$. Both GVA and the proposed algorithms are similarly initialized by a training sequence of 5 symbols. It suffice to note that the step-sizes used to update the channel parameters remain unchange. Interestingly the proposed approach using noisy initial channel parameters outperform the GVA with exact initial channel parameters over the range of doppler frequency. In particular, significant performance gain over GVA is observed at lower doppler frequency. However the gain diminishes as the doppler frequency increases to $400Hz$. The poorer

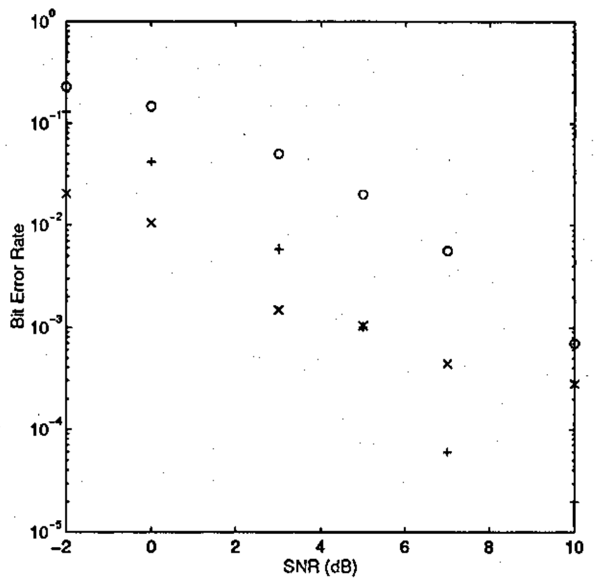

Figure 4.2: BER versus SNR. +: Algorithm II, o:GVA, ×: GVA with exact initial channel estimates

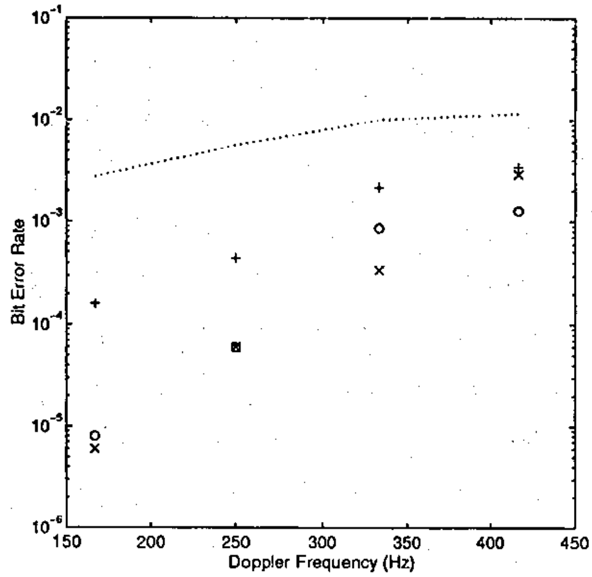

Figure 4.3: BER versus Doppler Frequency. SNR at 7dB. $\cdots$: GVA with noisy initial channel estimates. $+$: GVA with exact initial channel estimates. $\times$: Algorithm I. $\circ$: Algorithm II.

performance is probably due to the manifestation of the larger residual channel estimation and tracking errors from suboptimal choice of update step-size. Nevertheless, the proposed algorithms demonstrate encouraging results and it will be interesting to incorporate more sophisticated adaptive algorithms [65] and dynamic channel modeling, such as [35] and [66], to improve their sequence detection performance in very fast time-varying channels.

Figure 4.4 and 4.5 plot a typical example of the convergence trajectory of proposed algorithms and their corresponding number of erroneous symbol detection as a function of forward-backward iterations. It suffices to highlight that the cost function of Algorithm I and its corresponding num-

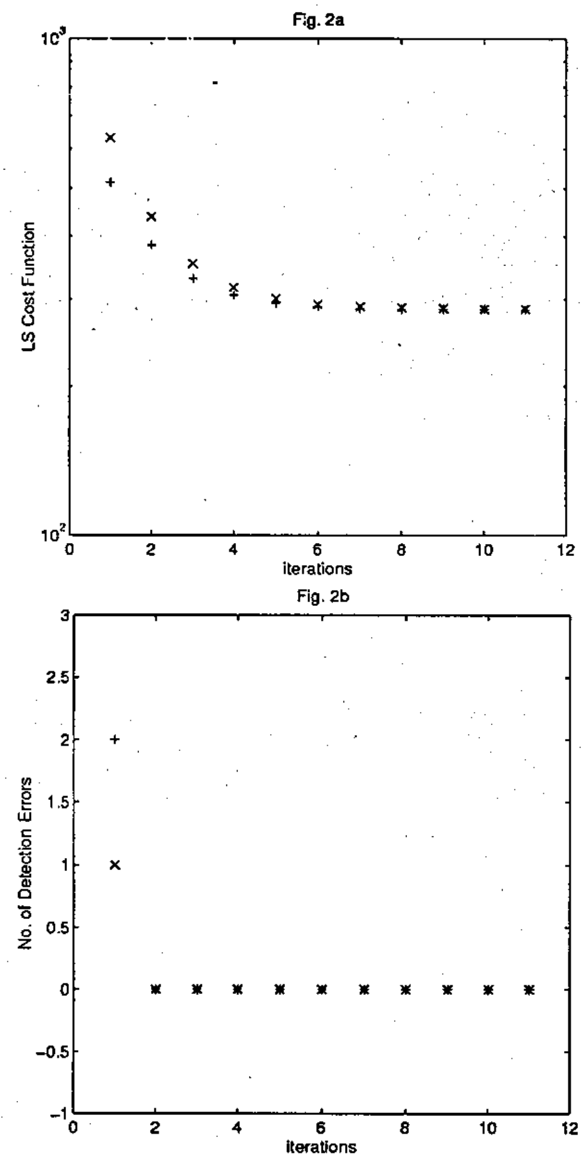

Figure 4.4: (a) Cost Function and (b) Number of Symbol Detection Errors vs. Iterations of Algorithm I. SNR: 3dB. The LS cost function after the forward and backward optimization at i^{th} iteration are denoted by '$\times$' and '+', respectively.

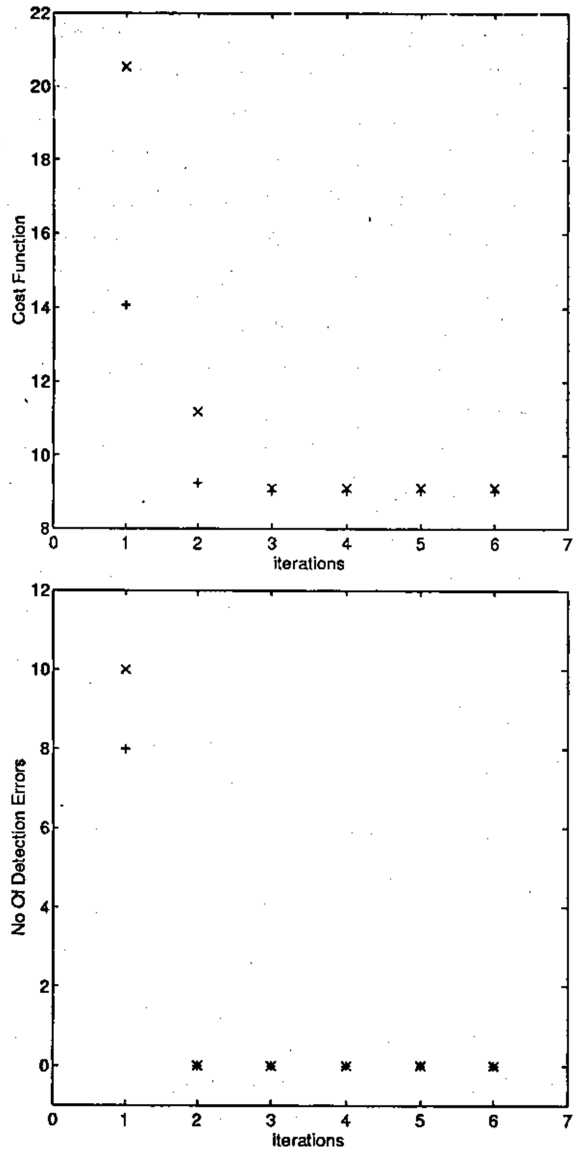

Figure 4.5: (a) Cost Function and (b) Number of Symbol Detection Errors vs. Iterations of Algorithm II. SNR: 3dB. The LS cost function after the forward and backward optimization at i^{th} iteration are denoted by '$\times$' and '+', respectively.

ber of symbol detection errors reduces monotonically with iteration number. Furthermore, the cost function after each forward(backward) optimization is always lower than the preceeding backward(forward) optimization. The monotonic reduction may not be the case for Algorithm II as the Toeplitz structure of the symbol matrix is not fully exploited. As illustrated in Figure 4.5a, the forward iteration has a slightly higher residual compared to the backward iteration. Nevertheless, we observe from our computational experience that this has negligible impact on the sequence estimation performance. Typically, both Algorithm I and II converge within 3 iterations.

4.5 Analysis of Computational Complexity

We analyze the relative computational complexity of GVA and proposed algorithm based on the number of complex multiplications and additions and is denoted by $(\alpha_{mul}, \alpha_{add})$. The number of computations involved for each LMS channel update based on (4.19) is $(2mML, 2mML)$ and $(mM(L+1)-1, mM(L+1))$ is required for VA metric computation. The number of computations involved for each LMS channel update based on (4.36) is $(2vmML, 2vmML)$. The number of metric computations at each time instant by GVA and the proposed Algorithm I are $K \times 2^{L+1}$ and 2^{L+1}, respectively. The number of channel updates required fof GVA is $K \times 2^L$. $(v(mM(L+1)-1)+2^{n''}(mM(L+1)-1), v(mM(L+1))+2^{n''}(mM(L+1)))$ computations are required for metric update in Algorithm II. Algorithm I and II require only 1 channel update at each time instant.

The total number of computations involved in GVA and the proposed

Algorithm I and II per symbol vector are $(K \times 2^{L+1}(mM(2L+1)-1), K \times 2^{L+1}(mM(2L+1)))$, $(2^{L+1}(mM(L+1)-1)+2mML, 2^{L+1}(mM(L+1))+2mML)$ and $(v(mM(3L+1)-1)+2^{n_{II}}(mM(L+1)-1), v(mM(3L+1))+2^{n_{II}}(mM(L+1)))$, respectively. ρ is the number of forward-backward iterations to achieve convergence. In this study, the number of computations per symbol for GVA and the Algorithm I and II ($\rho = 3$) are (1728, 1792), (1584, 1680) and (1422, 1488), respectively[3].

4.6 Conclusions

In this chapter, we have presented a semi-blind adaptive channel identification and equalization algorithm that jointly estimates the time-varying channel and performs sequence detection in a least squares framework. The simulation results are encouraging. They have demonstrated the proposed algorithms to be data-efficient, fast converging and capable of achieving good BER performance in a time-varying channel environment at relatively low SNR and with an extremely short training sequence. In addition, the proposed algorithms are computationally efficient. These features render the proposed algorithms to be potentially suitable for short burst data format communications where only extremely short training sequence can be made available in order to conserve bandwidth.

[3] In addition to the number of computations, implementation issues like the level of achievable pipelining and number of non-computational operations (e.g. memory fetch, conditional branching) will also have to be considered for real-time applications on DSP.

Chapter 5

Channel Equalization in the Presence of Strong CCI

5.1 Introduction

The radio propagation channels in wireless mobile communications are extremely harsh. Under the constraints of limited signal bandwidth and high signaling rate, signals propagating through the multipath radio channels will suffer impairments due to intersymbol interference (ISI). In TDMA cellular systems like GSM, the multipath induced ISI needs to be mitigated to achieve reliable sequence detection.

The notion of frequency reuse plays a key role in the improvement of the spectral efficiency in many cellular systems. The extent of the spectral efficiency improvement is however limited by the frequency reuse distance which is determined by the tolerable radio frequency interference such as co-channel interference (CCI). In addition, the choice of frequencies in the adjacent cells is also affected by the level of tolerable adjacent channel interferences (ACI) due to the limitation of the receiver's front end filtering. Unlike thermal noise, the effects of CCI as well as ACI cannot be removed by increasing the signal power. Increasing the signal transmission power in one cell will result in the correspondingly increase of the CCI/ACI level in the neighbouring cells. Current cellular systems mitigate and control these effects through careful frequency planning and allocation.

The spectral efficiencies of current cellular systems need to be improved in order to meet future demands driven by the increasing number of subscribers and the continual need to enhance the wireless services. But with limited bandwidth resource, increasing the signalling rate will worsen the channel impairments due to multipath induced ISI and the reduction of frequency reuse distance will increase the level of CCI/ACI. In order to achieve the desired spectral efficiency, it is important to develop effective algorithms to curtail the signal impairments due to ISI and CCI.

This chapter addresses the problem of channel identification and equalization of TDMA based digital cellular mobile communications in the presence of signal impairments due to ISI and CCI/ACI. In the past few years, a number of algorithms have been suggested. For example in [33] [34], the problem is approached from a classification perspective by exploiting the finite alphabet property of the information sequence. While the assumptions made in their formulations are very general, these algorithms typically require long training sequence. This may render them unsuitable for mobile communications applications where short burst formats are used. Optimum diversity combining algorithms that mitigate the effects of ISI and CCI using minimum mean square criterion were suggested in [41] [42] [49].

With the assumption of prior knowledge of CCI parameters, Wales uses a superstate trellis approach to jointly estimate the data sequences of the signal of interest (SOI) and co-channel interference [38]. In [39] [40], space-time algorithms are proposed for the case of unknown channels. Therein, the SOI and CCI channels and their associated data sequences are jointly identified and detected. Although these algorithms provides optimal solution (in bit error rate sense), they require the SOI and CCI to be bit-synchronous. Also, their receiver structures can become prohibitively complex when the channels are highly dispersive or when the number of dominant CCI is large.

In [46], Bottomley and Jamal proposed a space-only maximum likelihood sequence detection algorithm that uses the second order statistics of the radio frequency interference and noise. The significance of this approach is that the CCI and SOI need not be synchronous nor does it require prior knowledge of the number of CCI and their modulation waveforms. However it requires the base-stations of the SOI and CCI to be time-slot synchronized. As pointed out in [47], this assumption can easily be met in pico- and micro cellular applications. Under the ideal condition of Gaussian interference, this approach achieves optimal sequence detection [48].

In most applications of [46], the channel matrix and the interference+noise covariance matrix need to be estimated. In [47], the channel matrix is least square estimated from the training data without assuming the presence of CCI. This is followed by the estimation of interference+noise covariance matrix based on the least squares estimated channel parameters. Under mild conditions, these estimates are asymptotically unbiased. Such asymptotical results are not very useful practically as most TDMA cellular systems use short data formats. When short training sequences are available in order to conserve bandwith, the estimated channel parameters and interference+noise covariance matrix (as in [47]) become highly biased in the presence of strong CCI. This can degrade the sequence detection performance.

In this chapter, we propose a spatial-temporal algorithm in the spirit of [46] [47] [48] whereby the radio frequency interferences are considered as stochastic processes. Central to our approach is the recognition of the following basic ideas.

- Temporal diversity can be gained by observing the channel outputs from a tapped delay line. Geometrically, the temporal diversity can be interpreted as the widening of the noiseless channel outputs.

- The FA properties or discreteness of the information sequence and the inherent algebraic(Toeplitz) structures of the channel output vectors and data sequence can offer additional information to the estimation of the channel parameters and the noise+covariance matrix.

The chapter is organized as follows. We first present the data model, assumptions and the problem statement. In the next section, we describe the proposed algorithm based on the ideas described earlier. Simulation results are presented in section III. In section IV, we analyze the complexity of the proposed algorithm. Finally, section V summarizes the chapter.

5.2 Data Model and Problem Formulation

The siqual received at the i^{th} antenna of a N-element antenna array is given by

$$x_i(t) = \sum_k h_i(t - kT_b)s_k + n_i(t). \tag{5.1}$$

where $h_i(t)$ is the combined impulse response (having finite support of length LT_b) which includes the transmit pulse shaping, multipath radio channel and receiver filter. s_k is the information symbol belonging to a finite alphabet set Ω and T_b is the symbol duration. Assuming the received signal is oversampled M times of the baud rate and the received samples are collected from N-antenna, the channel output vector in presence of co-channel interference can be written as

$$\breve{\mathrm{x}}(kT_b) = \Xi\breve{\mathrm{s}}_k + \breve{\mathrm{i}}(kT_b) + \breve{\mathrm{n}}(kT_b) \tag{5.2}$$

where

$$\begin{aligned}
\breve{\mathrm{x}}(kT_b) &= \Big[x_1(kT_b), \cdots, x_1((k + \frac{M-1}{M})T_b), \\
&\qquad \cdots, x_N(kT_b), \cdots, x_N((k + \frac{M-1}{M})T_b)\Big]^T && (5.3)\\
\breve{\mathrm{s}}_k &= [s_k, \cdots, s_{k-L+1}]^T && (5.4)\\
\breve{\mathrm{n}}(kT_b) &= \Big[n_1(kT_b), \cdots, n_1((k + \frac{M-1}{M})T_b), \\
&\qquad \cdots, n_N(kT_b), \cdots, n_N((k + \frac{M-1}{M})T_b)\Big]^T. && (5.5)
\end{aligned}$$

Ξ is the channel matrix given by

$$\Xi = \begin{bmatrix} h_1(0) & \cdots & h_1(-(L-1)T_b) \\ h_1(\frac{1}{M}T_b) & \cdots & h_1((-(L-1)+\frac{1}{M})T_b) \\ \vdots & \vdots & \vdots \\ h_M(\frac{M-1}{M}T_b) & \cdots & h_M((-(L-1)+\frac{M-1}{M})T_b) \end{bmatrix}. \tag{5.6}$$

The term $\check{\mathrm{i}}(t)$ is due to the radio frequency interference term. In cellular communications where CCI is the dorminating RFI, we can write

$$\check{\mathrm{i}}(t) = \sum_{i=1}^{N_{CCI}} \mathbf{G}_i \mathbf{b}_i(t) \tag{5.7}$$

where $\mathbf{G}_i$ and $\mathrm{b}_i(t)$ are the channel matrix and symbol vector associated with the i^{th} CCI.

In this chapter, we shall assume the following:

- **A1**: The desired and interference channel responses remain stationary over the time-slot. This assumption is valid in most GSM radio channels and indoor applications. The extension to time-varying channels is beyond the scope of this chapter.

- **A2**: The desired and interferring signals are time-slot sychnronized. This is a reasonable assumption, particularly in micro and picocells wireless applications where time-slot (not symbol) synchronized base-stations can be easily maintained.

- **A3**: The signal of interest and the CCI are uncorrelated.

- **A4**: The interference is a zero mean process.

With the model of (5.2) in hand, the problem considered in this chapter can be succinctly stated as follows:

"Given the sampled channel output vectors collected over the time-slot, determine the channel parameters and the information sequence."

5.3 Proposed Channel Identification and Equalization Method

The spatial-temporal measurements can be written as

$$\begin{aligned} \mathbf{x}(kT_b) &= \mathbf{C}(\Xi)\mathbf{s}_k + \mathbf{I}(kT_b) + \mathbf{n}(kT_b) \\ &= \mathbf{C}(\Xi)\mathbf{s}_k + \mathbf{w}(kT_b) \end{aligned} \tag{5.8}$$

where

$$\mathbf{x}(kT_b) = \left[\check{\mathbf{x}}^T(t) \cdots \check{\mathbf{x}}^T((k-m+1)T_b)\right]^T \tag{5.9}$$

$$\mathbf{s}_k = [s(t) \cdots s(t-L-m+2)]^T \tag{5.10}$$

$$\mathbf{I}(kT_b) = \left[\mathbf{i}^T(t) \cdots \mathbf{i}^T((k-m+1)T_b)\right]^T \tag{5.11}$$

$$\mathbf{n}(kT_b) = \left[\check{\mathbf{n}}^T(kT_b) \cdots \check{\mathbf{n}}^T((k-m+1)T_b)\right]^T \tag{5.12}$$

$$\mathbf{w}(kT_b) = \mathbf{I}(kT_b) + \mathbf{n}(kT_b). \tag{5.13}$$

Note the $\mathbf{C}(\mathbf{\Phi})$ is a matrix operator that generates a block Toeplitz matrix from $\mathbf{\Phi}$. The advantage of utilizing spatial temporal measurements will be explained later in this chapter. By **A1**, the N-snapshots collected over the time-slot can be written as

$$\mathbf{X} = \mathbf{C}(\Xi)\mathbf{S} + \mathbf{W} \tag{5.14}$$

where

$$\mathbf{X} = [\mathbf{x}(kT_b)\ \mathbf{x}((k+1)T_b)\cdots\mathbf{x}((k+N-1)T_b)] \tag{5.15}$$

$$\mathbf{S} = [\mathbf{s}_k\ \mathbf{s}_{k+1}\cdots\mathbf{s}_{k+N-1}] \tag{5.16}$$

$$\mathbf{W} = [\mathbf{w}(kT_b)\ \mathbf{w}((k+1)T_b)\cdots\mathbf{w}((k+N-1)T_b)]\,. \tag{5.17}$$

We begin by assuming the interference+noise to be zero mean Gaussian process of unknown covariance $\mathbf{R}_{ww}$. The maximum likelihood (ML) estimation of the channel parameter matrix Ξ and the symbol matrix $\mathbf{S}$ can be achieved by optimizing the following likelihood functional:

$$\left\{\hat{\Xi}, \hat{\mathbf{S}}, \widehat{\mathbf{R}}_{ww}\right\} = \arg\min_{\Xi,\mathbf{S},\mathbf{R}_{ww}} \mathbf{V}(\Xi, \mathbf{S}, \mathbf{R}_{ww}) \tag{5.18}$$

where

$$\mathbf{V}(\Xi, \mathbf{S}, \mathbf{R}_{ww}) = \mathrm{Tr}((\mathbf{C}(\Xi)\mathbf{S} - \mathbf{X})^H \mathbf{R}_{ww}^{-1}(\mathbf{C}(\Xi)\mathbf{S} - \mathbf{X})) + N \log |\mathbf{R}_{ww}|. \tag{5.19}$$

As one may have noticed. the matrix structure and FA properties of the unknown symbol matrix offer an useful structural constraint to the problem addressed here. The FA property of the transmitted data limits the noiseless channel outputs to a discrete set and related to the symbol matrix through the channel parameter matrix. The Toeplitz FA symbol matrix limits the transition of the symbol vectors from one time instant to another, hence, the transition to another noiseless channel output vector will also be limited to an even smaller set. The interferences may not follow the Gaussian statistics and the *true* likelihood function is not likely to be available in practice. Hence, the likelihood function derived in (5.18) can only be perceived as an approximation to the *true* likelihood function.

Geometrically, the interference and noise can be approximated to be ellipsoidally distributed around the noiseless channel outputs. This approximation has demostrated to be useful in similar applications such as [45] [33] [34] [60]. In this case, the joint identification of the channel parameters and the detection of the data sequence can be perceived geometrically as follows:

Find a "valid" sequence of noiseless channel outputs (generated from the hypothesized channel parameter and symbol matrices) and interference+noise covariance matrix that minimize the Mahalanbolis distance from the sequence of observed channel outputs vectors.

Mathematically speaking, we have

$$\left\{\widehat{\Xi}, \hat{\mathbf{S}}, \widehat{\mathbf{Q}}\right\} = \arg\min \operatorname{Tr}\left((\mathbf{X} - \mathbf{C}(\Xi)\mathbf{S})^H \widehat{\mathbf{Q}}(\mathbf{X} - \mathbf{C}(\Xi)\mathbf{S})\right) + N \log|\widehat{\mathbf{Q}}| \quad (5.20)$$

where $\mathbf{Q}$ is an appropriate weighting matrix describing the ellipsoidal distribution of the interference and noise. The second term in (5.20) can be perceived as the "*regularizing*" term since choosing $\mathbf{Q} = \mathbf{0}$ results in a trival solution. Naturally, the optimal choice of $\mathbf{Q}$ for Gaussian interference is $\mathbf{Q} = \mathbf{R}_{ww}^{-1}$.

The motivation of utilizing the spatial temporal measurements is to exploit the temporal diversity gain from observing the channel outputs through a tapped delay line. We shall illustrate this by the following example. The channel impulse responses of the signal of interest,Ξ_{SOI}, and the co-channel interference, Ξ_{CCI}, are given by

$$\Xi_{SOI}(z) = [0.3\ 0.8\ 0.3] \quad (5.21)$$

$$\Xi_{CCI}(z) = [0.2\ 0.9\ 0.5], \tag{5.22}$$

respectively. We assume the transmitted symbols are limited to the FA set $\Omega \in \{-1, 1\}$. The Mahalanbolis distance between two channel outputs is defined as

$$d_{i,j} = (\mathbf{c}_i - \mathbf{c}_j)^H \mathbf{R}_{ww}^{-1} (\mathbf{c}_i - \mathbf{c}_j) \tag{5.23}$$

$$\mathbf{c}_{(\cdot)} = \mathrm{C}(\Xi_{CCI}) \mathrm{s}^{(\cdot)}. \tag{5.24}$$

$$\mathbf{R}_{ww} = \alpha_{CCI} \mathrm{C}(\Xi_{CCI}) \mathrm{C}\Xi_{CCI})^H \sigma_s^2 + \sigma_n^2 \mathbf{I}. \tag{5.25}$$

$\mathrm{s}^{(\cdot)} \in \Omega^{m+L-1}$. α_{CCI} is the level of co-channel interference. σ_s^2 and σ_n^2 are the signal and noise power, respectively. Due to the Toeplitz structure of the symbol matrix, the channel outputs at the next time instant, say from $\mathrm{x}(kT_b)$ to $\mathrm{x}((k+1)T_b)$, will be limited by the valid transitions of the symbol vectors, s_k to s_{k+1}. For example, the transition of $\mathrm{s}_k = [1\ 1\ 1\ 1\ 1]^T$ to s_{k+1} will be limited to $[1\ 1\ 1\ 1\ 1]^T$ and $[-1\ 1\ 1\ 1\ 1]^T$. Figure 5.1 illustrates the temporal diversity gain as a function of m with $\alpha_{CCI} = 1$. The normalized temporal diversity gain is defined as the ratio of distance of temporal window m with the distance with $m = 1$. We note from Figure 5.1 that with increasing m, the distance between the noiseless channel outputs becomes larger. However this is a diminishing gain. In this example, the temporal diversity gain diminishes after $m \geq 4$. Figure 5.2 plots the temporal diversity gain as a function of the α_{CCI} with temporal window fixed at $m = 3$. It shows the advantage of temporal diversity in the presence of strong CCI. Note that the gain diminishes as $\alpha_{CCI} \to 0$. This indicates that in the absence of CCI, observing the channel output from a tapped delay line will not offer

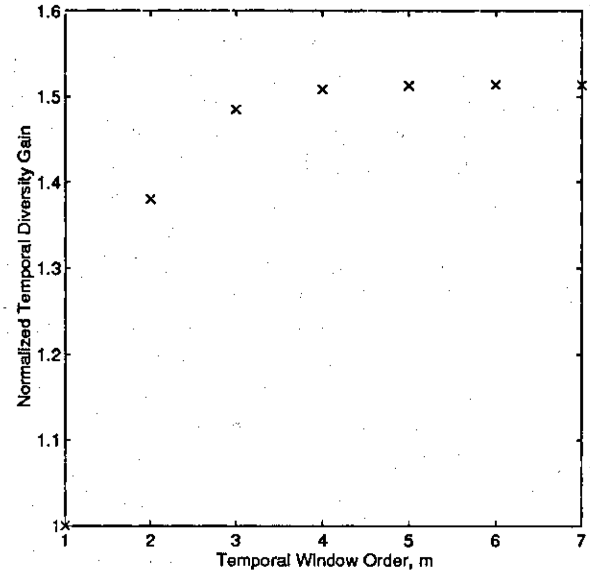

Figure 5.1: Temporal Diversity Gain versus Temporal Window Length

any advantage but further complicate the computational structure of the receiver.

In summary, we approach the problem of joint channel identification and sequence detection by optimizing the likelihod function in (5.20) with the exploitation of temporal diversity, the inherent matrix structure and the FA property of the unknown symbol matrix. Central to our approach is the recognition that

- R1: Temporal diversity can be gained from observing the channel outputs vectorally from a tapped delay line.
- R2: The FA property of the unknown data sequence and its inherent algebraic structure and relationships with the noiseless channel outputs

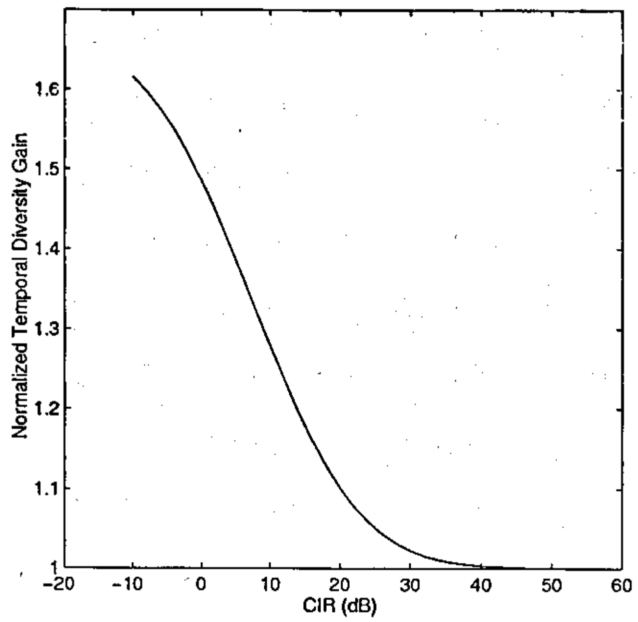

Figure 5.2: Temporal Diversity Gain versus CCI Level: $m = 3$

provide a powerful constraint.

It is important to note that many TDMA based wireless cellular communications systems utilize short data format. For example, GSM and IS-54 transmits with time-slots approximately equivalent to 150 symbols. With short training sequence length, the employment of asymptotics may no longer be useful. The approach proposed herein can alleviate this problem by utilizing R1 and exploiting R2 to jointly identify the unknown channel parameter, interference+noise covariance and symbol matrix. In particular, the channel parameter and interference+noise covariance matrix are estimated with data not limited to the training sequence but from the intrinstic information embedded entire data packet.

5.3.1 An Estimation Algorithm

The likelihood function (5.18) is a highly nonlinear function of continuous and FA constrained parameters. Such an optimization problem can be solved by applying the alternating minimization (AM) procedure. Basically, AM minimizes the cost function by optimizing it with respect to (*w.r.t*) a subset of the parameters while the remaining parameters, previously estimated, are held fixed. By cyclically minimizing *w.r.t* each parameter subsets, the cost function will monotonically decrease to a local minimum. In general, global convergence will depend on the choice of initial estimates. This is a widely used approach for optimizing highly nonlinear multi-value cost functions in many applications such as [52][53][54][59].

In this chapter, we adapt the AM concept and derive an iterative reweighting alternating minization (IRAM) algorithm to solve the problem represented in (5.18). IRAM comprises of the following basic steps to estimate Ξ, $\mathbf{S}$ and $\mathbf{R}_{ww}$. Beginning with a suitable initial estimates of Ξ and $\mathbf{R}_{ww}$, the symbol matrix $\mathbf{S}$ is computed by optimizing

Step 1

$$\widehat{\mathbf{S}} = \arg \min_{\mathbf{S}\in\Omega^{(m+L-1)\times N}} \mathrm{Tr}\left((\mathbf{C}(\widehat{\Xi})\mathbf{S} - \mathbf{X})^H \widehat{\mathbf{R}}_{ww}^{-1}(\mathbf{C}(\widehat{\Xi})\mathbf{S} - \mathbf{X})\right) \tag{5.26}$$

where $\widehat{\mathbf{S}}$ is constrained as a Toeplitz matrix of finite alphabet entries.

Step 2 Next (5.18) is updated with the estimated symbol matrix and by minimizing Ξ *w.r.t* (5.18), we have

$$\mathrm{vec}(\widehat{\Xi}) = \mathbf{\Phi}^{\dagger}(\widehat{\mathbf{S}})\mathrm{vec}(\widehat{\mathbf{R}}_{ww}^{-1}\mathbf{X}) \tag{5.27}$$

where

$$\Phi(\widehat{\mathbf{S}}) = \left(\widehat{\mathbf{S}}^T \otimes \widehat{\mathbf{R}}_{ww}^{-1}\right) \mathbf{P} \tag{5.28}$$

$(\cdot)^\dagger$ and $\otimes$ denote pseudo-inverse and kronecker product, respectively. vec($\mathbf{A}$) vectorizes $\mathbf{A}$ by stacking its columns into a vector and $\mathbf{P}$ is a full rank selection matrix such that vec($\mathbf{C}(\Xi)$) = $\mathbf{P}$vec(Ξ).

Step 3 The interference+noise covariance matrix can be updated from the error residual based on the latest estimates of Ξ and $\mathbf{S}$ by

$$\begin{aligned} \widehat{\mathbf{W}} &= \mathbf{X} - \mathbf{C}(\widehat{\Xi})\widehat{\mathbf{S}} \\ \widehat{\mathbf{R}}_{ww} &= \frac{1}{N}\widehat{\mathbf{W}}\widehat{\mathbf{W}}^H. \end{aligned} \tag{5.29}$$

After *Step 1* and *2*, $\widehat{\Xi}$ and $\widehat{\mathbf{S}}$ will converge towards, but not necessary to the final converged values. In *Step 3*, $\widehat{\mathbf{R}}_{ww}$ is refined thereby conditioning the cost functional towards better estimation of Ξ and $\mathbf{S}$. Thus, by alternatingly minimizing (5.18) with *Step 1* and *2*, and refining the cost function by reweighting with the interference+noise covariance matrix computed in *Step 3*, $\widehat{\Xi}$ and $\widehat{\mathbf{S}}$ will monotonically converge to a local minimum solution. A detailed discussion on the convergence is deferred to the appendix at the end of this chapter.

Sequence Detection

Symbol detection by exploiting the Toeplitz structure of $\mathbf{S}$ can be achieved with the application of the Viterbi algorithm. This can be computationally expensive to implement, particularly with the spatial-temporal channel matrix. For example with $m = 3$, $L = 3$ and $K = 2$ level signalling, the number of states in the trellis will amount to $K^{m+L-1} = 32$. In this chapter, the Toeplitz structure of the symbol matrix is *slightly* relaxed. We use a symbol by symbol detection approach that constrains S to be *partially* Toeplitz[43][44] in the following manner:

Given the tentative detection of the k^{th} symbol vector

$$\widehat{\mathbf{s}}_k = [\widehat{s}_k \cdots \widehat{s}_{k-L-m+2}]^T \tag{5.30}$$

and estimated channel matrix $\widehat{\Xi}$, the tentative detection of the $(k+1)^{th}$ symbol vector is given by

$$\widehat{s}_{k+1} = \begin{bmatrix} \widehat{\phi}_f \\ \widehat{\phi}_{fb} \end{bmatrix} \tag{5.31}$$

where

$$\widehat{\phi}_f = \min_{\phi_f \in \Omega^{n_{ff}}} \mathrm{Tr}\left(\mathbf{\Gamma}^H \widehat{\mathbf{R}}_{ww}^{-1} \mathbf{\Gamma}\right) \tag{5.32}$$

$$\mathbf{\Gamma} = \mathbf{x}((k+1)T_b) - \widehat{\Xi} \begin{bmatrix} \phi_f \\ \widehat{\phi}_{fb} \end{bmatrix}.$$

$$\widehat{\phi}_{fb} = [\widehat{\mathbf{s}}_k]_{k-n_{ff}+1 \cdots k-L-m+3,1} \tag{5.33}$$

with $[\mathbf{A}]_{i \cdots k,l}$ denoting a vector whose elements are extracted from the l^{th} column and i^{th} to k^{th} row of the matrix $\mathbf{A}$.

Proposed Algorithm

The proposed method is summarized as follows:

1. The received channel output matrix and the corresponding symbol matrix consist of the information (of length P) and training sequence (of length N^{Tr}), and are given by $\mathbf{X} = [\mathbf{X}_{Tr}\ \mathbf{X}_{Data}]$ and $\mathbf{S} = [\mathbf{S}_{Tr}\ \mathbf{S}_{Data}]$.

2. Based on previously estimated $\widehat{\mathbf{R}}_{ww}$ and $\hat{\Xi}_{WLS}$, estimate $\hat{\mathbf{S}}_{Data}$ with constraints **C2** and **3** from

$$\begin{aligned}\hat{\mathbf{S}}_{Data} &= \arg\min_{\mathbf{S}_{Data}} \operatorname{Tr}\left(\mathbf{\Delta}^H \widehat{\mathbf{R}}_{ww}^{-1} \mathbf{\Delta}\right) \\ \mathbf{\Delta} &= \mathbf{C}(\hat{\Xi}_{WLS})\mathbf{S}_{Data} - \mathbf{X}_{Data}\end{aligned} \tag{5.34}$$

by

- For $k = 0 \cdots P-1$
- Estimate $\hat{s}_{k+1} = [\hat{\phi}_f^T \ \hat{\phi}_{fb}^T]^T$ from (5.33) with $\Xi = \hat{\Xi}_{WLS}$ and $\mathbf{R}_{ww} = \widehat{\mathbf{R}}_{ww}$.
- End

3. Estimate Ξ_{WLS} from $\mathbf{X}$ by

$$\operatorname{vec}(\hat{\Xi}_{WLS}) = \mathbf{\Phi}^{\dagger}(\hat{\mathbf{S}})\operatorname{vec}(\widehat{\mathbf{R}}_{ww}^{-1}\mathbf{X}) \tag{5.35}$$

4. Compute

$$\widehat{\mathbf{W}} = \mathbf{X} - \mathbf{C}(\hat{\Xi}_{WLS})\hat{\mathbf{S}} \tag{5.36}$$

and update

$$\widehat{\mathbf{R}}_{ww} = \frac{1}{N}\widehat{\mathbf{W}}\widehat{\mathbf{W}}^H. \tag{5.37}$$

5. Repeat step 3-5 until convergence, if possible.

The channel parameters $\hat{\Xi}_{WLS}$ and the interference+noise covariance can be initialized with its least square estimates from the training data that assumes the absence of CCI:

$$\operatorname{vec}(\hat{\Xi}_{WLS}) = ((\mathbf{S}_{Tr} \otimes \mathbf{I})\mathbf{P})\operatorname{vec}(\mathbf{X}_{Tr}) \tag{5.38}$$

where $\mathbf{X}_{Tr}$ are the channel output vectors due to the training preamble $\mathbf{S}_{Tr}$. The interference+noise covariance, $\mathbf{R}_{ww}$, is then computed as in (5.36) and (5.37).

A similar procedure is used in [47] to estimate the channel parameters and the interference+noise covariance from the training data[1]. The estimates of Ξ and $\mathbf{R}_{ww}$ are asymptotically unbiased. When $N^{Tr} \to \infty$, we have

$$\begin{aligned} \mathrm{E}\left(\widehat{\Xi}_{LS}\right) &= \mathrm{E}\left(\mathbf{X}\mathbf{S}^{\dagger}\right) \\ &= \mathrm{E}\left(\left(\Xi\mathbf{S}+\mathbf{W}\right)\mathbf{S}^{\dagger}\right) \\ &= \Xi + \mathrm{E}\left(\mathbf{W}\mathbf{S}^{\dagger}\right) = \Xi. \end{aligned} \tag{5.39}$$

The equality results from **A3** and **4** where

$$\mathrm{E}\left(\mathbf{W}\mathbf{S}^{\dagger}\right) = \mathrm{E}\left(\mathbf{W}\right)\mathrm{E}\left(\mathbf{S}^{\dagger}\right) = \mathbf{0}. \tag{5.40}$$

Hence the estimated interference+noise covariance, $\widehat{\mathbf{R}}_{ww}$, is also asymptotically unbiased. As remarked earlier, such asymptotical results are not useful in many mobile applications as the time-slots of the data packets are very short. Hence, incorporating a long training sequence will severely limit the system's spectral efficiency. On the other hand, if Ξ and $\mathbf{R}_{ww}$ are not determined accurately, the estimation errors can result in poor sequence detection.

5.4 Simulation Examples

We present the results of simulations in this section. We use the TU channel profile described in [24] and assume a two element antenna array. To illus-

[1]The approach used in [47] did not exploit temporal diversity

trate the core ideas, we shall assume the data to be BPSK, $\Omega \in \{-1, 1\}$, transmitting at bit rate of 277kbs. The fading parameters are assumed to be independent between paths but are held constant over each burst. However, they are independently generated from burst to burst. The following parameters are fixed unless otherwise stated. We set training and data sequence length to be $N^{Tr} = 15$ and $P = 150$, respectively. We assume the SOI and a CCI impinge the antenna array from mean direction of arrival of 0 and 60 degrees. The multipath angles are randomly generated. We also assume that each signal path (angle) is angularly spread with distribution of $N(0, 30)$ due to local scatterers. The channel parameter matrix is generated based on the structured channel model described in chapter 2. The signal to noise ratio is 10dB.

In Figure 5.3, we show the BER achieved by IRAM with CIR ranging from $-15dB$ to $7dB$. Algorithms based on MMSE criterion[61], interference ratio combining (IRC)[46] and hybrid 2-Stage approach[62] are used to benchmark the proposed algorithm. The results are averaged directly over 5000 independent trials. The performance gains of the proposed algorithm are encouraging. For example, at 2% raw BER, IRAM achieved $5dB$ gain over IRC. Figure 5.3 also displays the BER performance of the conventional Viterbi based sequence detector. It clearly demonstrates the significant performance loss due to the presence of CCI. Note that the MMSE linear equalizer outperforms the conventional Viterbi sequence detector over the range of CIR. This is due to the dominance of the CCI over ISI.

The convergence properties of the proposed algorithm are examined next. In Figure 5.4, we plot a typical example of the cost function, channel estima-

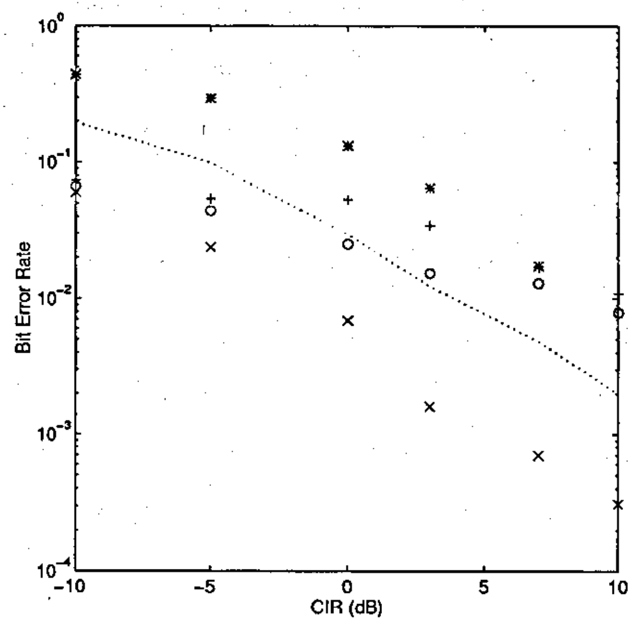

Figure 5.3: BER versus SNR. ×: IRAM, o: Hybrid 2-Stage Approach, ···: IRC, ∗: MLSD and +: MMSE

tion error and the number of erroneous detections as a function of iterations. Notice the incremental improvement of the channel estimates and sequence detection with the number of iterations.

In Figure 5.5, we examine the BER performance of IRAM and IRC with exact and estimated initialization over a range of CIR. It is interesting to note that IRAM with estimated channel parameter matrix and interference+noise covariance has similar performance compared to IRC with exact initialization. It also suffices to note that significant performance can be gained ($\approx$ 5dB) with better estimation of the channel parameters and the interference+noise covariance matrix.

Figure 5.6 displays the BER performance of the IRAM and IRC as a function of training length overhead, N^{Tr}. This graph demonstrates the importance of good initial estimates of the channel parameter matrix and interference+noise covariance. We observe an order of magnitude of gain is achieved in IRAM when the training length is 50 as compared to 15. This result shows that better initial estimates lead to better BER performance suggesting the need for more data efficient approaches of estimating these parameters. One approach to achieve this is to exploit *possible priors* like the modulation waveforms first proposed in [63] and later in [64]. Another approach is to apply the parametric channel estimator suggested in [35][36][10]. If permitted at system level, the training waveforms of SOI and CCI may be made as orthogonal as possible to allow for better estimation of the channel parameter matrix and the interference+noise covariance matrix.

Figure 5.7 shows the BER performance of the IRAM improves with the length of the information sequence, P. The result indicates that little im-

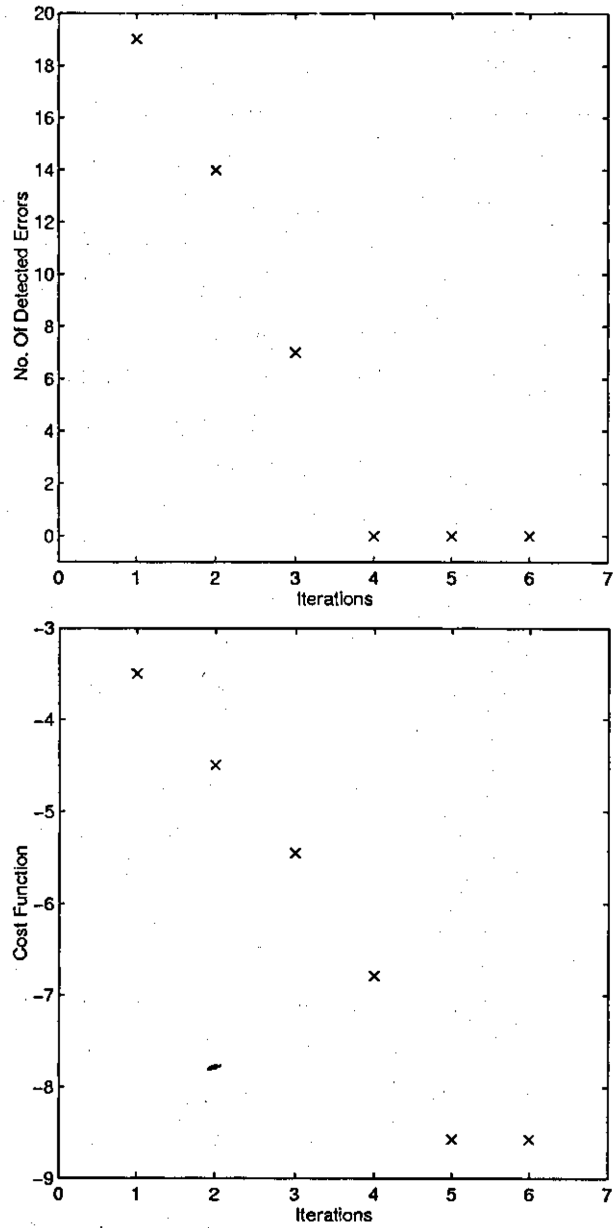

Figure 5.4: (a) Detection Error versus Iterations, (b) Cost Function versus Iterations

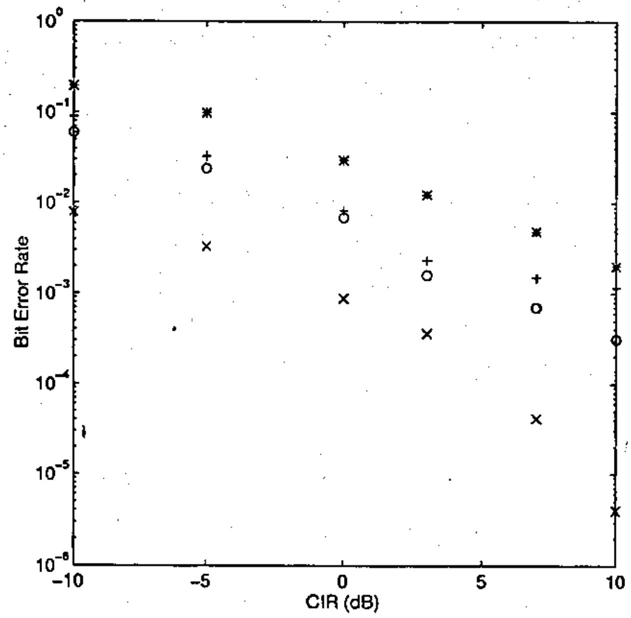

Figure 5.5: BER versus SNR. ×: IRAM with exact initalization, o: IRAM with estimated initialization, +: IRC with exact initialization, ∗: IRC with estimated initialization.

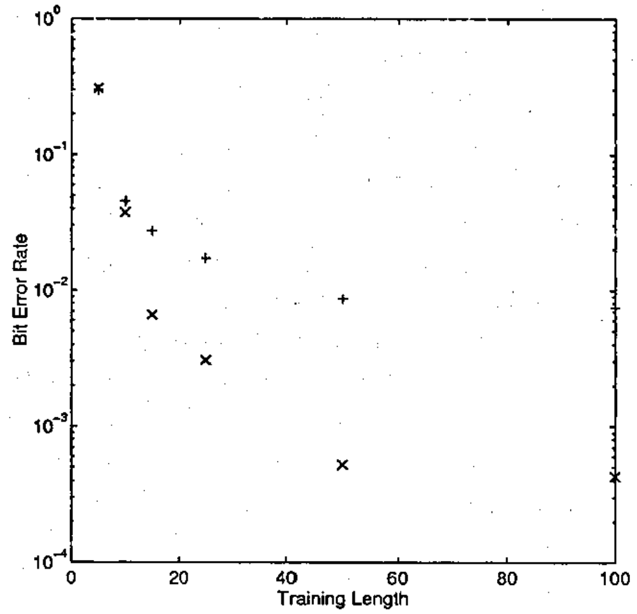

Figure 5.6: BER versus SNR. $\times$: IRAM and $+$: IRC

provement in performance can be achieved, perhaps only when the information sequence is extremely long. In Figure 5.8, we investigate the effects of direction of arrival of the CCI. The results show that the performance of the IRAM and IRC remained somewhat constant over principal quadrant. This may not be the case for DF-beamformer approaches.

5.5 Concluding Remarks

In this chapter, we consider the problem of channel identification and equalization in the presence of strong CCI. We propose an algorithm that identifies and equalizes ISI channels in the presence of strong multipath based on a least squares framework. The proposed algorithm does not require

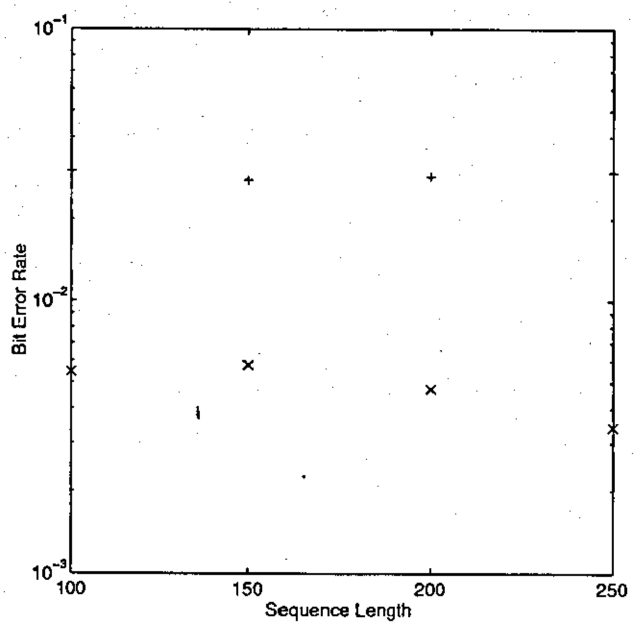

Figure 5.7: BER versus Information Sequence Length. ×: IRAM and +: IRC

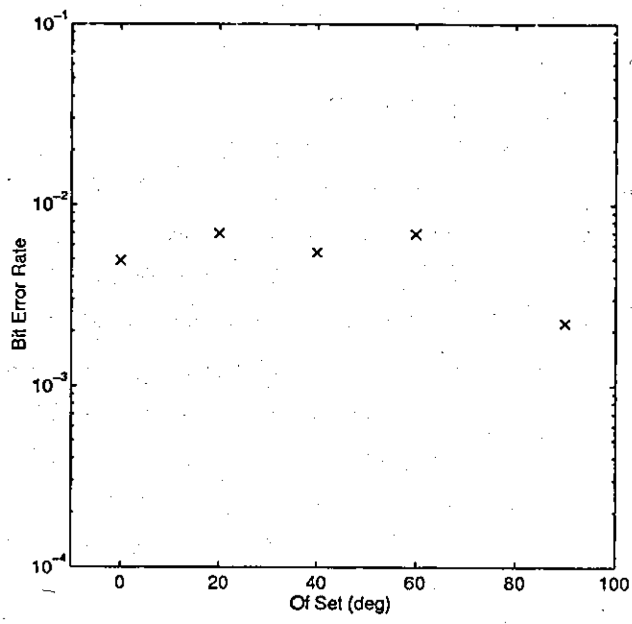

Figure 5.8: BER versus Offset Angle. $\times$: IRAM

knowledge of the number of interferers nor their structural information but requires time-slot synchronization. This requirement however can be easily achieved in cellular systems using small cells such as micro- and pico-cells. The potential performance gains suggested by the simulation results have been encouraging.

5.6 Appendix: Convergence Analysis

Let $\mathbf{S}_c$ and Ξ_c be the solution of a local minima. Also, let $\mathbf{S}^{(i)}$, $\Xi^{(i)}$ and $\mathbf{Q}^{(i)}$ denote, respectively, the estimated symbol matrix, channel matrix and interference+noise covariance after the i^{th} iteration. In the next iteration, we have

$$\mathbf{S}^{(i+1)} = \min \ \mathrm{Tr}\left((\mathbf{C}(\widehat{\Xi}^{(i)})\mathbf{S} - \mathbf{X})^H \widehat{\mathbf{Q}}^{(i)} (\mathbf{C}(\widehat{\Xi}^{(i)})\mathbf{S} - \mathbf{X})\right) \tag{5.41}$$

and followed by

$$\Xi^{(i+1)} = \min \ \mathrm{Tr}\left((\mathbf{C}(\Xi)\mathbf{S}^{(i+1)} - \mathbf{X})^H \widehat{\mathbf{Q}}^{(i)} (\mathbf{C}(\Xi)\mathbf{S}^{(i+1)} - \mathbf{X})\right). \tag{5.42}$$

We have

$$\left|\mathbf{S}_c - \mathbf{S}^{(i+1)}\right| \ \leq \ \left|\mathbf{S}_c - \mathbf{S}^{(i)}\right| \tag{5.43}$$

$$\left|\Xi_c - \Xi^{(i+1)}\right| \ \leq \ \left|\Xi_c - \Xi^{(i)}\right|. \tag{5.44}$$

The matrix $\mathbf{Q}^{(i+1)}$ is updated by

$$\mathbf{Q}^{(i+1)} = \left(\frac{1}{N}(\mathbf{C}(\widehat{\Xi}^{(i+1)})\mathbf{S}^{(i+1)} - \mathbf{X})(\mathbf{C}(\widehat{\Xi}^{(i+1)})\mathbf{S}^{(i+1)} - \mathbf{X})^H\right)^{-1}. \tag{5.45}$$

It follows that

$$\left|\mathbf{Q}_c - \mathbf{Q}^{(i+1)}\right| \leq \left|\mathbf{Q}_c - \mathbf{Q}^{(i)}\right|. \tag{5.46}$$

From (5.44),(5.44) and (5.46), the estimated $\widehat{\mathbf{S}}$, $\widehat{\Xi}$ and $\widehat{\mathbf{Q}}$ by iterative reweighted alternating minimization will approach their corresponding converged values.

Chapter 6

Summary and Conclusions

6.1 Summary

The radio spectrum is a limited resource. With the increasing demand for higher data rates, many wireless communications systems, with their present spectral efficiencies, are expected to be conjested to their capacities in the near future. This presents a major challenge for researchers and developers in wireless technology to develop novel system concepts and techniques aimed at improving spectral efficiency and achieving higher capacity within a limited spectrum.

The radio propagation channels in wireless mobile communications are extremely harsh. The signal that travels from the transmitter to the receiver through a multipath channels suffers impairments due to intersymbol interference and co-channel interference. Intersymbol interference (ISI) and co-channel interferences (CCI) are two major obstacles to high speed data transmission in wireless TDMA networks. Unlike thermal noise, these effects cannot be removed by increasing the signal power. As a result of relative motion between the transmitters and receivers, ISI and CCI become non stationary.

This thesis is divided into three parts. The first part formulates a convenient model for the space-time multipath channel. Starting from the continuous time domain, a vector space-time channel model parameterically described by signal path power, directions and times of arrival was developed. Compact expressions relating the array manifold of the antenna array and time manifold of the modulation waveform were derived. This development leads to the notion of *block space-time manifold.* When certain identifiability conditions are satisified, the noiseless vector channel outputs lie on a subspace constructed from a set of basis belonging to the block space-time manifold. This is an important observation as many high resolution array processing algorithms can be applied (with minimal modifications) to estimate the multipath channel parameters, in particularly directions and times of arrival. These are useful parameters in formulating optimum transmit beamforming strategy as well as mobile localization services. This parameter estimation problem was treated in Chapter 3. We presented a maximum likelihood estimator and derived subspace fitting algorithms such as weighted subspace fitting and MUSIC estimators to estimate the multipath directions and times of arrival. The MUSIC estimator offers significant computational simplicity over the WSF and ML estimator, but compromises in estimation performance. The usefulness of the proposed approach is demonstrated with numerical examples.

The second part of this thesis deals with the problem of identification and equalization of time varying channels. The main technical challenges addressed in this chapter are the development of channel identification and equalization algorithms for wireless mobile TDMA networks using short burst data formats. These technical challenges are:

1. Ability to track the time-varying channel.

2. Only require an extremely short or no training sequence for initial channel estimation.

3. Data efficient and fast converging due to short burst data format.

4. Perform adequately at relatively low SNR.

The problem considered here is one of semi-blind identification and equalization of time-varying channels where a short training sequence is used to obtain the initial channel estimates. Unlike conventional adaptive channel equalization methods, we addressed the problem of channel acquisition, tracking and equalization jointly. We approached the problem by exploiting the richness of the inherent structural relationship between channel parameters and data sequence by repeated use of available data through a forward-backward optimization procedure. Numerical results showed that the proposed approach has significant performance gains over conventional methods.

The final part of this thesis addressed the problem of identification and equalization of communications channels in the presence of strong co-channel interference. In chapter 5, we proposed a spatial-temporal algorithm that the interference+noise were used to provide the appropriate weighting. This is optimal if the interference+noise statistics are Gaussian. But in practice, this is not likely. It is therefore interesting to examine other metrics such as l_p norms as alternatives since such norms are expected to be more robust against non-Gaussianity.

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