Zero-based blind channel estimation and equalization

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Zero-Based Blind Channel Estimation and Equalization

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Due to multipath propagation characteristics of frequency-selective channels, inter-symbol interference (ISI) is a major obstacle in high speed data transfer. At high speeds of data transfer, blind estimation is also necessary to fully utilize the available bandwidth. Therefore, blind channel estimation and subsequent equalization are necessary at the receiver to combat ISI. In this thesis, zero based blind channel estimation and equalization algorithms are proposed.

For point to point communication systems, a single input single output (SISO) finite impulse response (FIR) channel model is used to describe the equivalent baseband system. Channel coefficient estimation and channel zero estimation for a minimum phase (MP) FIR channel is initially presented. It is shown that parameter estimation based on channel zeros is a natural and efficient way to estimate the channel coefficients. Furthermore, the estimation performance of the proposed algorithms through this approach can reach the bounds of blind channel parameter estimation.

Based on the development of MP channel parameter estimation, blind channel parameter estimation algorithms for non-minimum phase (NMP) channels are also

investigated. Initial channel zeros, obtained by second order statistics based methods, can be correctly located using higher order information of the received signal. The proposed algorithms use advantages of both second order statistics and higher order statistics.

For multiple-receiver systems, a single input single output (SIMO) channel model is exploited. The proposed SISO NMP channel parameter estimation methods are extended to the parameter estimation of SIMO channel. Here all zeros of all sub-channels are determined by using the cross-relationship between individual sub-channels.

It is well known that an equalizer at the output can be used to combat ISI and recover the unknown transmitted signal in high fidelity. Based on the estimated channel zeros, novel equalizer designs for SISO and SIMO channels are presented in the later part of the thesis. These equalizers belong to the categories of zero forcing (ZF) equalizer, minimum mean square error (MMSE) equalizer, and decision feedback equalizer (DFE). Traditionally, all equalizers are realized in FIR form as this is a guaranteed stable architecture. An efficient, stable infinite-impulse response (IIR) form for hardware implementation is also discussed in the thesis for reducing the length of equalizers. It is shown that the use of IIR architecture saves hardware register usage by a significant amount. An example of equalizer application in underwater acoustic (UWA) communication channel is provided which is designed by considering the characteristics of the UWA channel. For block transmission systems, a bi-directional zero based decision feedback equalizer (BizDFE) is also proposed.

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Chapter 1

Introduction

In recent years, the demand for high-speed data transfer has been increased in wireless communications, such as radio communications, underwater acoustic communications. In high-speed wireless communications, the multipath propagation property of the channel and the limited bandwidth result in an unwanted superposition of the transmitted symbols at the receiver. This is referred as inter-symbol interference (ISI). ISI may result in high error rate in symbol detection. In order to combat ISI and obtain reliable communication, channel estimation and subsequent equalization are necessary at the receiver. Channel parameters can be estimated using a training sequence, however, training estimation will cause a loss of available bandwidth. Blind channel estimation and equalization have received a large amount of research interests in the recent two decades, due to the fact that no additional bandwidth is required for blind channel estimation.

1.1 Motivation

For channel estimation, there are three types of estimators [1]. Most commonly, a training sequence is used for channel estimation. The channel impulse responses are

estimated from the known training sequence via a cross correlation at the receiver. This mode is called training-estimation. Obviously, it is quite effective in the case that the channel does not change over time. It is especially not efficient in rapidly varying channels due to the requirement of frequent training. In a multipoint network, whenever a link from the server to one of the benthic stations is interrupted, it is not feasible for the server to start sending a training sequence to re-establish a particular link. During online transmission impairment monitoring, the training sequences are not supplied by the transmitter. Fortunately, the second method, blind channel estimation method, needs no training sequences. The importance of blind estimation is strongly supported by practical needs. The channel impulse responses are estimated while information sequences are being transmitted. The major advantage of this technique is the improved bandwidth utilization for time varying channels. The third method of channel estimation falls in between the training based techniques and blind channel estimation techniques. In digital communications, some known symbols are incorporated into transmission to assist the detection operation, such as in synchronization. This mode of channel estimation uses not only the known data and its corresponding observation, but also the observation of the unknown data. Although it causes loss of some bandwidth, it takes the advantages of training based technique as well as blind channel estimation technique. But the known sequence is not available under all conditions and, thus, this semiblind method cannot be used in all systems. Based on these reasons, blind channel estimation and equalization have drawn a large amount of research interests.

Blind channel estimation can be mainly grouped into two categories: the nonparametric and parametric approaches. The nonparametric methods usually result in estimation having high variances and low resolution. The parametric methods assume that the data obey a probabilistic model of known structure and estimate the unknown parameters of the underlying model via the available data. The goal of parametric methods is to achieve the optimal accuracy in estimation. The parametric method of channel estimation is discussed throughout this thesis.

Consider a single user channel model, a model usually suitable for describing point to point communication systems, e.g. time division multiple access (TDMA) systems,

and global system for mobile (GSM) systems [1], are known as single input single output (SISO) channels. If the channel parameters are varying slowly, the channel can be modeled as a linear time-invariant model. The wireless communication channels can be assumed to be a finite impulse response (FIR) model. And the estimation of FIR parameters has been a research problem in signal processing [2], control system identification [3], and even can be dated back over fifty years. New estimation algorithms continue to be proposed. However, all existing algorithms have one or more drawbacks. In this dissertation, we propose channel estimation methods to achieve better performance with robust property under various system conditions. It is noted here that existing solutions for FIR channel estimation in literature can be classified into two categories: minimum phase (MP) system estimation; nonminimum phase (NMP) system estimation. Algorithms suitable for both MP and NMP channel estimation are discussed in this thesis.

MP channel estimation can be traced back to the MA (Moving Average) model parameter estimation. There are a large amount of existing algorithms for MA parameter estimation. For example, the Durbin method [4] using SOS (second order statistics) information—a method of maximum likelihood estimation (MLE) [5], estimates the MA model coefficients using a long AR (Autoregressive) process to approximate the observed MA process. The estimated AR parameters using the MLE technique are then mapped into MA parameters. But it is shown that this estimation is a biased estimator. Stoica [6] proposed the best algorithm appearing in the literature for MA model coefficients estimation based on the SOS property. As noted in [6], "The MA estimation algorithms proposed here are computationally fast, statistical accurate, and reliable. None of the previously available algorithms for MA estimation (methods based on higher-order statistics include) shares all these desirable

properties" [6]. Given the observed MA covariance sequences, the method minimizes a least square (LS) spectral criterion for covariance sequences via semidefinite programming to obtain MA model parameters. In order to solve the minimization problem and achieve good performance, an overparametrized signal (OS) approach is adopted. This approach overcomes the usual convergence problem. It is noted that the OS method has the best performance among all the reported MA parameter estimation algorithms, especially when the zeroes are close to the unit circle. The common character of all the above noted methods is that they use SOS information. The advantages of SOS based methods are that a small number of samples are used with a low computation load in the channel estimation algorithm and thus suitable for estimating rapidly varying parameters. As is well known the second order correlation sequence does not contain phase information, thus, the use of SOS based methods can only be in MP channel estimation. In this case, it is always assumed that the channel zeros are inside the unit circle.

Note that structure of FIR channel model and MA system model are very close. The only difference between the MA model and the FIR channel is the type of input signal. For the MA model, the input signal is assumed to have Gaussian statistics. Whereas, the input for the FIR model is non-Gaussian, and Gaussian noise is added at the receiver side of the model. If only second order statistical information is involved, we note that algorithms suitable for MA model parameter estimation can be used in MP FIR channel estimation as well.

Since the knowledge of the channel phase is very critical for data communications, the identification of NMP systems has also received considerable attention during the last two decades. Numerous blind techniques on NMP system identification, estimation and deconvolution have been proposed in the literature. These approaches

can be broadly divided into three categories. The first one is the estimation of parameters by higher-order statistics (HOS) of the observed data [7]. If the signal is non-Gaussian, Lii and Rosenblatt [8] has shown that it is possible to obtain the correct phase information from output data using higher order statistics information. Since then, a variety of HOS based methods have been proposed and investigated. For example, channel estimation methods based solely on HOS appear in [7-10]. Higher order cumulants are also blind to any kind of Gaussian processes [10]; hence, cumulant-based signal processing methods are inherently immune to colored Gaussian measurement noise, whereas correlation-based methods are not. Consequently, cumulant-based methods boost signal-to noise ratio when signals are corrupted by Gaussian measurement noise. However, the major drawback of HOS based methods is that they require longer data lengths for estimation and they possess higher computational complexity. Furthermore, if a random process is symmetrically distributed, then its third-order cumulant is zero; hence, the fourth-order cumulant (trispectrum) is needed in the parameter estimation [7]. Since the signals in wireless communications, e.g. the BPSK (Binary Phase Shift Keying), QAM (Quadrature Amplitude Modulation) signals are symmetrically distributed [11], the estimation requires the use of fourth order cumulant or trispectrum [12], thus even longer data length is necessary. The second category of blind channel estimation is based on the signal distribution at the equalizer output. Linear inverse filters can be used to equalize the observed data to recover input signal and estimate the characteristics of the unknown channel, such as in [13-15]. The third blind estimation methods are based on second order cyclostationary statistics (SOCS) based methods proposed by Tong et al. in [16]. If the sampling rate at the receiver is higher than the baud rate, it is identified as fractional sampling. The SOCS method also contains the phase

information. So SOCS based methods can be used in the NMP system estimation [16-19]. But when the oversampling at the receiver is not an available option of the application, the method cannot be used.

In order to exploit advantages of both SOS information and HOS information, Lii and Rosenblatt [8] have noted that combining SOS with HOS can provide the solution to blind channel estimation problem, but they did not propose any algorithms. Reference [9] extends this idea by using the full fourth order cumulant to locate zero positions. As noted earlier, the calculation of HOS is time-consuming and has high computational complexity. Using other computationally low methods, such as HOS slice information and finite alphabet information, the channel zero positions also can be located without resorting to the full fourth order cumulant. These techniques will be discussed in detail in later chapters of the thesis.

When multiple sensors are used at the receiver, or oversampling is used with one sensor at the receiver, the communication system is referred as a single input multiple output (SIMO) channel model [11, 20, 21]. SIMO channel model exploits the channel diversity of the transmission system. It is noted that the SIMO transmission can improve the performance significantly, especially in severely fading channels. The SIMO systems are also attractive as they can be blindly identified using second order statistical information. A number of techniques for SIMO blind channel estimation has been proposed since the work of Tong et al. [16]. One can refer to [21] for details of these methods. Fractionally spaced equalization using CMA (constant modulus algorithm) is adopted for SIMO channel equalization. However, we note that developing efficient signal processing methods with low complexity for channel estimation and equalization still presents challenging issues [15]. In this thesis, simple

but efficient techniques for joint SIMO channel estimation and equalization are also proposed.

It is known that the purpose of communications is to recover the channel input symbols from the received signal. The received signal usually suffers from channel multipath effect and additive white Gaussian noise. The solution is to design a receiver that provides a means for compensating or reducing the ISI in the received signal. The compensation for the ISI is done at the equalizer [11]. It is well known that training-estimation based equalizers can be used to recover the transmitted signal, but training based methods are not always feasible. In most communication systems the channel characteristics are not only unknown a priori but also the channel response is time-variant. Self-recovering or adaptive blind equalization techniques which are based on initial adjustment of the coefficients without using training sequence has gained more attention in recent years starting from the work of Sato [22]. Rules of equalizer parameter adjustment are critical points of designing a blind equalizer. Substantive algorithms for automatically adjusting the equalizer coefficients to optimize a specified performance index and to adaptively compensate for time variations in the channel characteristics are proposed over the years. Due to the property that HOS is blind to Gaussian noise, HOS based cost functions have been the most popular methods in designing blind equalizers (e.g. [13, 15, 23]) since 1980. Direct channel equalization and indirect equalization via symbol estimation are commonly adopted in most practical systems. For indirect method, after the channel parameters are estimated, the used techniques can be categorized into three kinds: maximum-likelihood sequence equalizer (e.g. MLSE equalizer [24]); decision feedback equalizer (DFE) [25]; and linear equalizer (inverse filter) e.g. [26, 27].

With regard to the computational complexity, the linear equalizer and DFE have a lower complexity, although DFE is a little bit more complicated than a linear equalizer; MLSE has the highest complexity among the three categories. With the purpose of designing low complexity equalizers, the linear equalizer and the DFE are investigated, and the MLSE is not discussed in the thesis.

Linear equalizer has two main categories. One is the zero-forcing (ZF) equalizer, which is simple and easy to implement. However, it usually enhances the noise effects. The other is the minimum mean square error (MMSE) equalizer. It can avoid the noise enhancement and is especially useful under low signal to noise ratio (SNR) scenarios, but it requires additional information, such as the knowledge of the noise variance. Note however, that the MMSE design may increase the computational load due to the required additional optimization.

The most common nonlinear equalizer, which is more complicated than the ZF equalizer, but simpler than the MMSE design, is the use of a decision feedback equalizer (DFE). DFE design minimizes the mean square error between the input to the symbol decision threshold device and the detected transmitted symbol, and was originally proposed by Mosen [25]. Error propagation is inherent in the DFE equalizer, for example, when an error occurs at the receiver, it would be feedback causing undesirable compensation. Due to this, the probability of subsequent errors will increase, which usually results in error bursts. However, DFE is a good choice considering a compromise between hardware complexity and optimization complications.

SIMO equalization has recently shown wide applications. SIMO equalization based on the channel estimation can be found in [16, 18, 28-30]. Gesbert firstly proposed direct equalization for SIMO channel in [31]. It is followed by other direct

equalization techniques proposed in [32, 33]. SIMO equalization has a variety of applications in many fields, for example, application in wireless sensor networks can be found in [28]. It also can be applied in optical systems [29], and in underwater acoustics communications [34-36].

One of application areas for algorithms proposed in this thesis, is in underwater acoustic (UWA) communications. Compared to the radio wireless communication, blind channel estimation and equalization in the UWA communications still is a difficult task and has received less attention from the research community. The UWA environment is much more complicated and variant. Unlike digital communications via radio channels where data are transmitted by means of electromagnetic waves, underwater communications primarily use acoustic waves. The available bandwidth in an UWA communication channel is severely limited by transmission loss, which increases with both frequency and range. Within the limited bandwidth of UWA channel, high-speed acoustic communication systems typically require a much larger spectrum that may suffer from severe ISI due to the frequency-selective characteristics of the UWA channels, which may result in large ISI and large Doppler shift and spread in comparison with the radio channels. Underwater acoustic channels are generally characterized as fading multipath channels that are quite variable and depend on a variety of factors including ocean depth, the propagation path length and the location of the transmitter and receiver [36]. Also, they may suffer from multiple access interference (MAI) when multiple users share the common acoustic resource [37]. The UWA is promising since the applications have been transferred from military usage to commercial application, such as oil exploration, environmental data collection [38]. To improve the data transfer capacity while keeping a high data quality is without exception considered to be the most challenging task of an UWA

communication system. Efficient means of data communication techniques are required in UWA channels. More and more research works about UWA channels estimation and equalization are proposed, such as [39, 40].

1.2 Objectives

Although there are a substantial number of algorithms for channel parameter (or transfer function) estimation in literature, sometimes the interest is on the estimation of roots (zeros) of the unknown channel, such as in DOA estimation [41], spectrum analysis [42], and speech communication [43]. The performance analysis of zero estimation can be found in [42, 44]. The distribution function of wireless communication channel zeros is presented in [45]. All these show that the zero-based channel estimation and equalization is possible. It is also noted here that the channel zero information plays an important role in the channel estimation because channel identifiability and estimation bounds can be directly related to the zero locations as shown in Appendix B.

One of the major objectives of this dissertation is to propose simple and reliable blind channel estimation algorithms for SISO and SIMO channels. According to the need of the applications, the aim of blind channel estimation can be summarized as, I) The method can be used under all conditions, that is, it has no convergence problems. II) Due to the time varying nature, the channel estimation algorithm only can use small or medium-size number of samples. The mean square error of the estimated parameters should be a minimum value. III) The computational load should be low. IV) The complexity of the algorithm needs to be as simple as possible. Since full HOS cumulant can be used to identify the location of zeros which are obtained by SOS based methods [8, 9], zero-based channel estimation techniques are investigated

in the thesis. These techniques are expected to fulfill all the above noted requirements of blind channel estimation, since the best SOS based method can be adopted together with low computational complexity information, such as HOS slice, finite alphabet information, and other information. Furthermore, in order to evaluate the performance of the proposed algorithms in SISO and SIMO channel estimation, the bounds of channel estimation are also required.

The second objective of this work is to develop equalizer algorithms based on the channel estimation results obtained in the initial objective. Minimization of the detection errors is the main function of the receivers. The equalizers used in practice can be divided into three categories: training, blind and semiblind [1]. The training and semiblind equalizers are designed through the use of both the received and training or pilot signals at the expense of system resource (e.g. bandwidth). Due to the benefit of resource (bandwidth) saving and no need of training phases, extensive research on blind techniques have been reported, which usually exploit the properties of the transmitted symbol sequences and the received signal's statistical properties or the transmitted constellation properties. There are two ways for blind equalizer design: one may directly design an equalizer using the received signal, the other way of designing equalizer is based on the estimated channel impulse response. As the design of an optimal detector requires the knowledge of the channel, the second way is preferred in the design of equalizers as done in this thesis.

We note here that the zero-based equalizer design is attractive as zeros can be obtained once the channel is estimated. For this, there exist a number of efficient and robust zero estimation algorithms reported in the literature across numerous application areas. As shown later in the thesis, channel zeros information also simplifies the DFE implementation due to separate use of minimum phase and

maximum phase zeros in the DFE feed-back and feed-forward structure [46]. As such, equalization via channel zero locations can be justified as a natural approach to equalizer design.

The third objective of this dissertation is to demonstrate the use of proposed channel estimation algorithms in UWA communications and investigate the application of spatial diversity equalizers in UWA communication. In this regard, efficient means of data communication techniques are proposed for the UWA channels.

1.3 Major Contribution of The Thesis

In this thesis, zeros based channel estimation and equalization algorithms for SISO and SIMO channels are proposed. At first, techniques for blind estimation of SISO channels are presented. Via the use of a zero forcing equalizer, three efficient and reliable blind estimation algorithms are proposed. The first method is based on the combination of SOS and HOS cumulant slice. Second method is based on the combination of SOS and the kurtosis property of the transmitted signal. The third method utilizes the SOS information and the finite alphabet knowledge of the transmitted signal. SOS based methods provide efficient estimation of channel zeros from a very small number of samples, but as noted earlier, the estimates are phase blind. We show that the cumulant slice of HOS, kurtosis property and the FA information can be used to resolve the ambiguity of system zero location. The performance of the three estimation methods is compared and the complexity of algorithms is discussed. In the channel estimation, a linear residue zero-forcing equalizer based on the channel zeros is incorporated. It is then shown that the equalizer output could be exploited recursively to improve the estimation accuracy using the FA property of the transmitted signal. As all available information for blind

channel estimation is used, the proposed methods achieve a very high accuracy in blind channel estimation. This is elaborated by presenting the performance of the estimation methods. As the method inherently uses an equalizer, separate equalizer is not necessary. Thus, the approach is different to the conventional channel estimation and equalization methods.

The equalization performance of a SIMO receiver is superior to a SISO receiver as the SIMO model uses spatial diversity combination. The investigation of SIMO channel estimation and equalization is very important for high speed and reliable communication in particular in UWA communications. Based on the algorithms developed for SISO blind channel estimation, SIMO channel estimation algorithms are presented. It is shown that, given the polynomial correlation matrix (PCM) of the SIMO model, SIMO channel parameters can be estimated with a low computational complexity when a large number of samples are available and the additive noise power is low. However, when a small number of samples are available and/or a higher noise power is present, the performance of the use of PCM rapidly deteriorates. In order to overcome this difficulty, a least squares technique is used for SIMO channel estimation via the PCM. As a further improvement, it is also shown how the equalizer output resulting from the strongest subchannel can be used to estimate the other subchannels, via the use of a least squares technique. For the proposed algorithms, having common zeros among subchannels does not pose any difficulty in estimation.

In digital communications, the transmitted signal takes values only in a discrete and finite alphabetical set that is known at the receiver. This important a priori information has been proven extremely useful, however it is ignored in many exiting literature on channel estimation, such as in [1, 17, 26]. On the other hand, a method proposed by Benveniste et al. [23], utilizes the distributional information of the

unobservable signal to identify the nonminimum phase system. Blind system identification and deconvolution methods via finite alphabet (FA) information have also been investigated in detail by T.H.Li in [28, 47, 48]. An application of FA property of the channel estimation in OFDM systems can be found in [49]. In this work, we show that with the use of FA property in SISO and SIMO blind estimation, one can achieve the same estimation accuracy that can be obtained by training-sequence estimation.

To recover the unknown transmitted signal is the ultimate goal in the communication system. A series of novel approaches for channel equalization which uses the estimated channel zero information is presented in the later part of the thesis. It is shown how the estimated FIR channel zeros can be efficiently used in the design of three different equalizers: ZF equalizer, MMSE equalizer, DFE, for both SISO and SIMO channels. Simulations are used to indicate the performance differences of the designed equalizers.

In summary, followings are the novel contributions of the work:

- Blind channel coefficient estimation and channel zero estimation of MP channel are summarized in chapter 2.
- Algorithms for blind NMP channel coefficient estimation and channel zero estimation are proposed in chapter 3.
- SIMO channel parameter estimation algorithms are proposed in chapter 4.
- Channel zero based equalizers for SISO and SIMO channel models are discussed in chapter 5.

1.4 Organization of the Thesis

The dissertation is organized as follows:

Chapter 2 presents channel coefficient estimation and channel zero estimation for a minimum phase finite impulse response channel. A brief review of the methods for channel zero estimation is followed by a discussion of their performance. It is shown that the estimation of channel zeros is a good alternative way to estimate the channel parameters. At the end of the chapter, bounds for blind channel zero estimation for MP channels are presented. Thus, chapter 2 presents a basic framework for the work presented later in the thesis.

In chapter 3, blind channel parameter estimation algorithms for NMP SISO channels, using SOS combined with HOS cumulant slice, Kurtosis, FA property are discussed. Initial channel zeros obtained by SOS based methods, can be correctly located by using the above noted higher order information. The performance of the methods is compared in detail, by investigating the sensitivity of the proposed HOS cost functions. Zero-tracking property of the proposed algorithm in a slow time varying environment is provided.

In chapter 4, the proposed channel estimation methods are extended to SIMO channel models. At the beginning, the SIMO channel model and assumptions used are discussed. Then a brief introduction to existing SOS based methods for SIMO channel estimation is provided, e.g. the subspace method, the cross-relation method. In the proposed SIMO estimation algorithm, the first subchannel is estimated by the SISO techniques proposed in chapter 3. The zeros of the remaining subchannels can then be determined by other techniques, for example, using the cross relationship between individual subchannels. It is also noted that the Smith McMillan form is a powerful tool in SIMO channel analysis. The application and simulation results of the proposed SIMO estimation methods are given at the end of chapter 4.

Chapter 5 describes equalizer designs for SISO and SIMO channels. Equalizer is used to recover the unknown transmitted signal in high fidelity. All proposed equalizers in chapter 5 are based on the estimated channel zeros. For SISO channels, zero forcing (ZF) equalizer, minimum mean square error (MMSE) equalizer, decision feedback equalizer (DFE), are proposed and discussed. ZF, MMSE, DFE equalizers for SIMO channels are also presented. The similarity and difference between all equalizers are described in chapter 5. An efficient form for hardware implementation is provided by reducing the length of FIR equalizers, which saves hardware register usage by a large amount. Appendix C is provided to the chapter, where the linear convolution structure imposed by the channel is reversed by using a time reversal operation. This is done by reversing the time domain sequential order of the received samples prior to equalization. In doing so, the equivalent channel impulse response becomes a time-reversal of the actual channel impulse response as seen from the equalizer side. The zeros of time-reversed channel are the reciprocal of the original channel zeros. Based on this concept, a bi-directional zero based decision feedback equalizer (BizDFE) is proposed and its performance is discussed in the appendix C. An example of equalizer application in a UWA channel is provided, followed with a brief introduction to the characteristics of UWA channels. The use of spatial diversity equalization technique in UWA communications is elaborated, and the performance of such equalization is illustrated.

Finally, conclusions based on this research work and directions for future research are provided in chapter 6.

Chapter 2

Minimum Phase Channel Coefficient and Channel Zero Estimation

In this chapter, channel coefficient estimation and channel zero estimation for a minimum phase (MP) finite impulse response (FIR) channel are discussed. Error bounds for the channel coefficient and zero estimation are presented. They are useful for estimation performance comparison. It will be shown how the derived bounds can also be extended to non-minimum phase channel parameter estimation.

Section 2.1 describes the channel model and the assumptions used in this chapter. The channel model is expressed as a polynomial in channel coefficients or as a multiplication of several first order polynomials resulting from channel zeros. A brief review of existing second order statistics based methods for coefficient estimation is given in section 2.2. Techniques for finding roots of a polynomial are introduced here. The use of the autocorrelation function in estimating channel zeros is also shown. In section 2.3, minimum phase channel zero and channel coefficient estimation error bounds are presented. Simulation and comparison results for error bounds and parameter estimation are illustrated in section 2.4. In section 2.5, a summary of this chapter is presented. It is noted that the channel estimation algorithms and channel

equalizer designs appearing in subsequent chapters are all designed based on the concept of evaluating channel zeros. Therefore, channel zero estimation and the performance evaluation via the derived bounds present a basic framework for the work presented later in the thesis.

2.1 Channel Model & Assumptions

In this chapter, a single user channel is investigated. Such a channel is usually used in point to point communication systems, e.g. time division multiple access (TDMA), and global system for mobile (GSM) systems [1]. The channel is also known as a single input single output (SISO) channel. If the channel parameters are varying slowly, the channel can be modeled as a linear time-invariant system. For a continuous time communication system, the SISO channel can be shown as in Fig. 2.1.

Figure 2.1 The SISO channel model for a continuous time communication system

In this system, at first, random information symbols are mapped onto signal constellations at the transmitter. The mapped symbols are then pulse shaped within the transmit filter. Then the pulse shaped signals are modulated by a carrier frequency and transmitted through a frequency selective channel. At the receiver, demodulation is used to remove modulation. The received signal, which is corrupted by the additive noise, is filtered by a matched filter. The matched filter is matched to the transmitter waveform. From Fig. 2.1, the continuous-time received signal can be expressed as,

$$y(t) = x_n * f_T(t) * C(t) * f_M(t) + w(t) * f_M(t) = x_n * h(t) + w(t) * f_M(t) \quad (2.1)$$

where we have defined an equivalent frequency selective channel impulse response as,

$$h(t) = f_T(t) * C(t) * f_M(t) \quad (2.2)$$

The equivalent channel $h(t)$ is the convolution result of the transmitter filter, the analog channel and the matched filter. Due to sampling at baud-rate, both the input and output of the continuous time system are discrete signals at the symbol rate. Thus, an equivalent discrete time model can be realized based on the continuous-time communication system in Fig. 2.1. The system model is shown in Fig. 2.2, where the finite length discrete channel impulse responses $\{h(n)\}$ are obtained by sampling the continuous-time impulse response. If the signal $y(t)$ is oversampled, i.e. sampled at higher than baud-rate, the received signal will increase statistical information for channel estimation. (The use of over-sampled signal statistics will be discussed in Chapter 4.) According to the continuous-time system model, in the baseband digital (sampled) communication system, the information symbols are transmitted through a frequency selective digital channel. The channel output is corrupted by a discrete additive noise sequence at the receiver as shown in Fig. 2.2.

Figure 2.2 Block Diagram of an equivalent baseband digital (sampled) communication system

According to the SISO linear time-invariant model in Fig. 2.2, the relationship between channel input symbols $\{x(n)\}$ and the received signal $\{y(n)\}$ can be expressed mathematically as,

$$y(n) = \sum_{k=0}^L h(k)x(n-k) + w(n) \quad (2.3)$$

The transmitted symbols $\{x(n)\}$ are resulting from an independent identical distributed (i.i.d.) process with zero mean, that is independent to the additive zero mean Gaussian noise sequence $\{w(n)\}$. As the symbols belong to a finite-alphabet constellation, they posses non-Gaussian and stationary statistics. Let $H(z^{-1})$ represent the z-transform of the channel impulse responses $\{h(k)\}$. Usually, the finite length channel impulse responses $\{h(k)\}$ are unknown at the receiver and should be estimated by either using a training sequence or by using some blind channel estimation techniques.

Note that the channel transfer function can be expressed in a cascade form as the multiplication of first order polynomials given by,

$$H(z^{-1}) = \sum_{k=0}^L h(k)z^{-k} = \prod_{k=1}^L (1 - b(k)z^{-1}) \quad (2.4)$$

where $\{b(k)\}$ are zeros of the channel. Before we proceed to further discussion, the following assumptions on the channel are noted.

A1) The memory of the channel impulse response is finite, so that the channel can be modeled as a finite impulse response (FIR) filter. Without loss of generality, it is assumed that $h(n)=0$ for $n<0$ and $n>L$, and $h(0) \neq 0$, $h(L) \neq 0$.

A2) Define L as the memory order and it could be estimated by many existing methods. For example, Akaike information criterion (AIC) searches minimum AIC value for all possible model orders. However, it tends to overestimate the channel order. Conditional model estimator (CME) proposed by S.M. Kay in [50] is believed to be more consistent. One can refer to [51] for more detail discussion of channel order estimation.

A3) No zero of the channel appears on the unit circle.

Note that zeros $\{b(k)\}$ can be inside the unit circle or outside the unit circle, and the positions of the zeros determine the type of the communication channel. If all the

zeros are inside the unit circle then the channel is a minimum phase (MP) channel, while having all the zeros outside the unit circle makes it a maximum phase channel. However, in general channels are non-minimum phase (NMP), having zeros both inside and outside the unit circle. If a channel may have zeros outside the unit circle, it may not be severely fading if the zeros are far from the circle. Thus the estimation of channel zeros in proper location is important in real applications [41]. It is well known that autocorrelation sequence (second order statistics) is phase blind, and zeros inside the unit circle (minimum phase zeros) and their reciprocals outside the unit circle (maximum phase zeros) would produce the same autocorrelation sequence. Therefore, using the autocorrelation (second order) statistics, the minimum phase zeros can be located. And by proper relocation (as discussed in chapter 3) of the MP zeros, the NMP channel coefficients also can be estimated.

2.2 Estimation using Second Order Statistics (SOS)

2.2.1 Channel Coefficient Estimation

The aim of this section is to estimate the coefficients and zeros of an MP FIR channel. The only difference between the MA model and the FIR channel is the type of input signal. For the MA model, the input signal has Gaussian statistics. Whereas, the input for the FIR model is non-Gaussian, and Gaussian noise is added at the receiver side of the FIR model. If only second order statistical information is used, we then note that algorithms used for MA model parameter estimation can be used in MP FIR channel estimation as well.

As an example of MA model parameter estimation technique, the Durbin method is a linear procedure that produces suboptimal estimates for the MA parameters. The popularity of the Durbin algorithm stems from its simplicity and speed. The routine

finds the MA parameters from a linear least-squares technique that uses the coefficients of a higher order AR model. The process $\{y(n)\}$ in (2.3) can be approximated by the $AR(\infty)$ process as,

$$y(n) = -\sum_{k=1}^{\infty} a(k)y(n-k) + x(n) \quad (2.5)$$

where $\{a(k)\}$ are the impulse responses of the AR model. And $A(z^{-1})$ is the Z-transform of $\{a(k)\}$. It is noted that an $AR(N)$ process with $N \gg L$ is a good approximation to the $MA(L)$ process. There are many ways to estimate the AR parameters, such as Burg, Levinson, and Maximum-Likelihood. We do not discuss AR parameters estimation here. The MA model parameters can be obtained from AR model parameters as,

$$H(z^{-1}) = \frac{1}{A(z^{-1})} \quad (2.6)$$

Stoica [6] proposed the best SOS based algorithm appearing in literature for MA model coefficient estimation. The hypothetic covariance of the observed $\{y(n)\}$ can be obtained using following expressions,

$$r_{yy}(j) = \sum_{k=1}^{L+1} \sum_{p=1}^{L+1} u_k^T Q u_p \delta_{k,p-j} = \begin{cases} \sum_{k=1}^{L+1-j} u_{k+j}^T Q u_k & j = 0, \dots, n \\ 0 & j \geq n+1 \end{cases} \quad (2.7)$$

where u_k is the k^{th} column of the $(n+1) \times (n+1)$ identity matrix. The observed covariance of $\{y(n)\}$ is

$$\hat{r}_{yy}(j) = \frac{1}{N} \sum_{n=1}^{N-k} y(n)y^*(n+j) \quad (2.8)$$

where $Q = \bar{\eta}^T \bar{\eta} \sigma_x^2$ and $\bar{\eta} = [h(L) \ h(L-1) \cdots h(1) \ 1]$. In order to minimize the squared error between the observed covariance and hypothetic covariance in

polynomial time, overparametrize $\{r_{yy}(j)\}$ in a linear manner via the independent elements of Q is an alternative way. The method minimizes a least square (LS) spectral criterion of covariance sequences via semidefinite programming to obtain the MA model parameters. It is noted that the OS (overparameterized signal) method in [6] has the best performance of all the reported MA parameter estimation algorithms, especially when the zeroes are close to the unit circle.

The common character of the above methods is that they use SOS information, but as noted earlier the second order correlation sequence does not contain channel phase information. That is, SOS based methods can only be used in MP channel estimation.

2.2.2 Channel Zero Estimation

It is also of interest to estimate the zeros of the MA model as noted in [43, 44]. Equalizers based on channel zeros are applied in underwater acoustic communication in [52]. The direct method of estimating channel zeros is via the use of the estimated channel coefficients. Let $\{\hat{h}(k)\}$ be the estimated channel coefficients from an SOS based method, such as OS or Durbin method. The zeros of the channel can be found by computing the eigenvalue of the companion matrix of the coefficients vector [53].

The companion matrix M_c of the estimated coefficients vector $\{\hat{h}(k)\}$ is defined as,

$$M_c = \begin{bmatrix} -\hat{h}(1)/\hat{h}(0) & -\hat{h}(2)/\hat{h}(0) & \cdots & -\hat{h}(L)/\hat{h}(0) \\ 1 & 0 & & \\ & \ddots & \ddots & \\ & & 1 & 0 \end{bmatrix} \quad (2.9)$$

Using the property that the roots of a polynomial and the eigenvalue of its companion matrix are equal, the roots (zeros) of the channel can be obtained from,

$$[\hat{b}(1) \ \hat{b}(2) \cdots \hat{b}(L)] = \text{eig}(M_c) \quad (2.10)$$

where $\text{eig}(\cdot)$ denotes a function (e.g. in MATLAB) delivering the eigenvalues of a matrix.

The second method to find the channel zeros is via the use of the autocorrelation sequence of the received signal $\{y(n)\}$. The two-sided autocorrelation function (ACF), which is the Z-transform of the autocorrelation sequence, can be expressed as,

$$R_{yy}(z^{-1}) = \sum_{k=-L}^L r_{yy}(k) z^{-k} \quad (2.11)$$

where autocorrelation sequence $\{r_{yy}(k)\}$ is defined as,

$$r_{yy}(l) = E\{y(k)y^*(k+l)\} = \sigma_x^2 \sum_k h(k)h^*(k+l) + \sigma_w^2 \delta(l) \quad l = 0, \pm 1, \pm 2, \dots \pm L$$

and $*$ denotes the complex conjugate operator. Under the assumptions on the input signal stated in section 2.1 and without considering the additive noise, (2.11) can also be expressed using the channel transfer function as,

$$\begin{aligned} R_{yy}(z^{-1}) &= \sigma_x^2 H(z^{-1})H^*(z) \\ &= \sigma_x^2 \prod_k (1 - b(k)z^{-1})(1 - b^*(k)z) \end{aligned} \quad (2.12)$$

From (2.12), we can see that the autocorrelation sequence (second order statistics) of the received signal $\{y(n)\}$ contain the information of channel zeros and their reciprocals. Information on both minimum phase zeros and maximum phase zeros are inherent in ACF, since the roots of autocorrelation polynomial consist of channel zeros and their reciprocals, i.e.,

$$\text{roots}(R_{yy}(z^{-1})) = [b(1) b(2) \dots b(k) \ 1/b^*(1) 1/b^*(2) \dots 1/b^*(k)] \quad (2.13)$$

However, information about the actual zero location, that is, whether a channel zero is inside or outside the unit circle, can not be obtained from the ACF.

If the channel is a minimum phase channel, then by mapping the minimum phase zeros obtained from (2.10) or (2.13) into the polynomial coefficients using (2.4) the channel coefficients can be estimated. Vice versa, a maximum phase channel also can

be estimated. However, for a mixed phase channel, which is the more general case of communication channels, the problem is how to obtain the correct location of the channel zeros. A solution for finding zeros location is described in [54] in detail. Since blind estimation of MP channel coefficients and zeros via the SOS methods does not have the problem of zero location ambiguity, in this chapter, we use SOS based MP channel estimation performance as the benchmark for all NMP channels estimation.

2.2.3 Impact of Input Signal Gaussianity of the Durbin and OS methods

In this section, via simulation, we will investigate the Gaussianity of the input signal on the estimation performance of the unknown channel. In the simulations, six different random sequences with different probability distribution functions (PDF) are used as input signals. They are: 1) double-side exponential 2) uniform distribution (-1,1) 3) 4-QAM (Quadrature amplitude modulation) [11] 4) 8-QAM 5) 16-QAM 6) Gaussian. All input signals are zero-mean complex sequences. No Gaussian noise is added at the filter output. The estimation performances are evaluated via the normalized mean-square error (NMSE) defined as,

$$NMSE = \frac{\sum_{k=0}^L |h(k) - \hat{h}(k)|^2}{\sum_{k=0}^L |h(k)|^2}$$

The NMSE results of channel estimation by using Durbin and OS are as follows:

TABLE 2.1 THE NMSE RESULTING FROM DIFFERENT INPUT SIGNALS.

	exponential	uniform	4-QAM	8-QAM	16-QAM	Gaussian
Durbin	0.0024	0.0025	0.0024	0.0025	0.0024	0.0024
OS	0.0017	0.0018	0.0017	0.0018	0.0017	0.0017

The MP channel used in the simulation has zeros $\{0.5837 + 0.6615i, 0.5837 - 0.6615i, -0.6\}$. 2000 runs are used in the simulation and the number of samples for each run is 1024. From Table 2.1, we can see that performance

results are very similar for all different input signals. It is thus concluded that the input signal distribution has no impact on the two channel estimation techniques. And the two methods are suitable for FIR channel parameters estimation, regardless whether the input being a Gaussian or a non-Gaussian signal.

2.3 Bounds on Channel Coefficient and Channel Zero Estimation

This section presents a discussion on the estimation bounds for zero estimation and coefficient estimation of a minimum phase FIR channel. It is noted that the bounds on the zero estimation of an MA process can be obtained via the bounds of zero estimation of an ARMA process as shown in [44], with the assumption that the input signal probability density function (PDF) is a Gaussian distribution. Reference [44] only consider the case of zeros appearing in complex conjugate pairs. In this chapter, we extend that analysis for a more general case where zeros can appear on the real axis or as a complex conjugate pair. Based on the simulation results of the previous section, we would extend this bound for the case of non-Gaussian inputs signals (e.g. finite alphabet communication signals).

2.3.1 Error Bounds on Channel Zero Estimation

For an MA process, the Fisher information matrix for channel zero estimation can be expressed as,

$$I_b(m, n) = N \sum_{u=0}^{\infty} d_{m,u} d_{n,u} \quad (2.14)$$

where N is the number of samples used in the estimation. It can be easily shown that $d_{m,u}$ is the u^{th} coefficient of the following Z-transform as,

$$D_m(z^{-1}) = z^{-1} \prod_{k=1, k \neq m}^L (1 - b(k)z^{-1}) [H(z^{-1})]^{-1} \quad (2.15)$$

The proof is presented in appendix A. It is easy to obtain $d_{m,u}$ if the inverse filter

$[H(z^{-1})]^{-1}$ is expressed in the following partial fraction summation form,

$$[H(z^{-1})]^{-1} = \frac{1}{H(z^{-1})} = \sum_{k=1}^L H_k^B(z^{-1}) \quad (2.16)$$

where $H_k^B(z^{-1})$ is a branch transfer function corresponding to each zero. The minimum phase branches with amplitude of zero less than unity can be easily implemented by an M length FIR filter approximately. The realization details of $H_k^B(z^{-1})$ can be found in chapter 5. We will not dwell the details here, as they are same as in the zero-forcing equalizer design of chapter 5. Error bounds for channel zero estimation can be obtained using the Fisher information matrix in (2.14) as,

$$tr(I_b^{-1}) / \sum |h(k)|^2 \quad (2.17)$$

2.3.2 Error Bounds on Channel Coefficient Estimation

In a similar form to that in (2.14), the Fisher information matrix [55] for channel coefficients estimation can also be derived as,

$$I_h(m, n) = N \sum_{u=0}^{\infty} \tilde{d}_{m,u} \tilde{d}_{n,u} \quad (2.18)$$

$\tilde{d}_{m,u}$ is the u th coefficient of the Z-transform

$$z^{-m} [H(z^{-1})]^{-1} \quad (2.19)$$

The detail procedure for obtaining (2.18) can be found in appendix A. It is noted here that the Fisher information matrix in (2.18) is obtained under the assumption of having a high SNR. We also note that at low SNR,

$$E \left\{ \sum_{k=0}^L (h(k) - \hat{h}(k))^2 \right\} \approx E \left(\sum \hat{h}(k)^2 - \sum h(k)^2 \right) \approx \sigma_w^2 / \sigma_x^2 \quad (2.20)$$

Using (2.18) and (2.20), an approximate bound for the FIR channel coefficient estimation error in the presence of additive noise can be obtained as,

$$bound = (\sigma_w^2 / \sigma_x^2 + tr(I_h^{-1})) / \sum |h(k)|^2 \quad (2.21)$$

The above bound can be used for MP channel estimation performance comparison. It is also noted here that the above bound can be extended for the case when zeros are outside the unit circle, since the bound on channel coefficient estimation error in this case is obtained by considering an equivalent MP channel which has the same autocorrelation sequence as that of the NMP channel.

The following example gives a simple explanation. Three channels are presented here as: minimum-phase channel $H_1(z^{-1}) = (1 - az^{-1})(1 - bz^{-1})$, maximum-phase channel $H_2(z^{-1}) = (1 - az)(1 - bz)$, and mixed-phase channel $H_3(z^{-1}) = (1 - az^{-1})(1 - bz)$, with $|a| \leq 1$ and $|b| \leq 1$. Given the same input signal to these three channels, the output autocorrelation sequences are same as,

$$r(-2) = ab \quad ; \quad r(-1) = -(a+b)(1+ab) \quad ; \quad r(0) = 1 + a^2b^2 + (a+b)^2 \quad ;$$

$$r(1) = -(a+b)(1+ab) \quad ; \quad r(2) = ab$$

We can easily find the roots of autocorrelation sequence as

$$roots([r(-2) \ r(-1) \ r(0) \ r(1) \ r(2)]) = [a \ b \ 1/a \ 1/b]$$

From the autocorrelation sequence, channel zeros can be obtained if zero location information is known a priori. Assuming that the NMP zeros can be correctly located by using the autocorrelation function, $[H(z^{-1})]^{-1}$ can be realized for the NMP channel. The bound in (2.21) also can be applied for evaluating NMP channel coefficient estimation. Appendix B provides a detailed discussion on this.

2.4 Simulation Results and Comparisons

2.4.1 Channel Coefficient and Zero Estimation

In this section, simulation results are shown to illustrate the performance of Durbin and OS methods in comparison to the bounds derived in the previous section. At first, we compare these algorithms for coefficients estimation for an FIR channel having an input signal belonging to a 4-QAM constellation. The channel coefficient vector is $[1 \ -0.5674 \ 0.0778 \ 0.4670]$, all the zeros are inside the unit circle and are as same as those used in obtaining the results in Table 2.1. It is assumed that the SNR is high enough to ignore the noise effects at the input of the receiver. The number of samples is varying from 400 to 1600. The results are shown in Fig. 2.3. and Fig. 2.4, for channel coefficient estimation and channel zero estimation respectively.

Figure 2.3 The blind estimation results obtained by OS, Durbin and ACF are compared with the derived coefficient bound for MP FIR channel coefficient estimation.

Figure 2.4 The blind estimation results obtained by OS, Durbin and ACF are compared with the derived zero bound for MP FIR channel zero estimation.

We note that when there are a large number of data samples or the SNR is high enough, the ACF also can be used to estimate the channel coefficients and zeros. Although, the estimation with ACF is of lower accuracy, it is a much more computationally efficient technique than the other two methods. The highest accuracy is obtained by the OS method but at the expense of a higher computational complexity. In Fig. 2.3 and 2.4, the estimation performances are also compared with the derived bound for MP channel coefficient estimation and channel zero estimation.

2.4.2 Comparison with Higher Order Statistics based Estimation

It is well known that HOS based techniques can be used for proper location of the channel zeros without having the minimum phase – maximum phase ambiguity. In this section we would compare the previously noted SOS based OS method with a HOS based channel estimation technique. The HOS technique selected for comparison is the generalized weighted slice (GEWS) [56] algorithms which, arguably, is one of the best HOS based channel estimation techniques reported in the literature. The input signal and example channel are same as those in section 2.4.1. The additive noise is a white Gaussian sequence and the SNR in the simulation varies

from 2dB to 42dB. The number of samples is 1000. The estimation performance of SOS-based and HOS based algorithms is compared with the proposed bound for MP FIR channel coefficient estimation is shown in Fig. 2.5.

Figure 2.5 Estimation results obtained by SOS and HOS based algorithms compared with bound in (2.21) in MP channel coefficient estimation.

As noted earlier the bound in (2.21) can be used to evaluate the NMP channel estimation. The estimation performance for a NMP FIR channel is illustrated in Fig.2.6. The additive noise is white Gaussian sequence and the input signal is a 4-QAM signal. The channel transfer function is given by $H(z^{-1}) = 1 - 0.9z^{-1} + 0.385z^{-2} + 0.771z^{-3}$, having zeros $[0.75 + 0.85i \ 0.75 - 0.85i \ -0.6]$. Note that this channel is a widely quoted example used in the literature (e.g. in [56] and references therein), and the reciprocals of the maximum phase zeros are as same as the zeros of the previously discussed MP channel. For the SOS based method the channel estimation is achieved by assuming that the zeros can be correctly located [54]. From Fig.2.5 and 2.6, we can see that the derived bound in (2.21) provides us with a bound for channel estimation for both MP and NMP channels over a wide range of SNR. It should be stated here that a bound using (2.18) is obtained under a high SNR assumption, while the expression in (2.20) is only valid for low SNR conditions. Therefore, the expression in (2.21) is not accurate in the medium SNR

range. SNR is varying from 2dB to 40 dB. The simulation results also suggests that the SOS based technique is more accurate at high SNR while at low SNR the HOS based technique is the better choice.

Figure 2.6 Estimation results obtained by SOS and HOS based algorithms compared with bound in (2.21) in NMP channel coefficient estimation.

2.5 Summary

In this chapter, we have discussed exiting SOS based methods and compared their performance in minimum phase FIR channel coefficient and zero estimation via the use of only SOS information. It is noted that SOS based channel estimation algorithms have a lower computational complexity compared with HOS based techniques. The best SOS method, the OS method is the most complicated in comparison to Durbin and ACF based algorithms. The simplest method based on the ACF is suitable for channel estimation if the required accuracy is not too high.

It is also noted here that, unlike the work reported in the literature, the derived bounds for MP channel coefficients and zeros estimation do not require restrictions, such as that zeros should appear in complex conjugate. The derived bounds can also be extended for the evaluation of NMP channel estimation. Therefore, the derived

estimation bounds for MP FIR channels can be used as a benchmark for comparing various channel estimation algorithms discussed throughout this thesis.

Chapter 3

Blind Single Input Single Output Channel Parameter Estimation

Based on the discussion and developments in chapter 2, blind SISO channel estimation of an FIR channel is addressed in this chapter. The unknown channel can be a minimum phase or a non-minimum phase channel. Assumed MP channel zeros can be blindly obtained using techniques in chapter 2, the HOS information, kurtosis property and the finite alphabet (FA) information can then be used to solve the ambiguity in system zero location. Three efficient and reliable blind estimation algorithms are proposed here. The first method is using SOS and a slice of higher order statistics (HOS). The second method is based on the combination of SOS and

the kurtosis property of the transmitted signal, which is one point of the fourth order cumulant. The third method utilizes the SOS information and the FA knowledge of the transmitted signal. It is also shown that the equalizer output could be exploited recursively to improve the estimation accuracy using the FA property. As all available information is used in estimation, the recursive estimation achieves a very high accuracy in blind channel estimation. Performance of the various estimation methods is also discussed.

3.1 Introduction

For NMP system estimation methods, there are a number of estimation categories, such as maximum likelihood methods, and moment matching methods. The details of these methods are not dwelt on here, but for a comprehensive review of blind channel estimation methods one is referred to [1]. A common approach in developing well-behaved algorithms for parameter estimation is the use of second-order statistics (SOS) [4, 6]. However, SOS based methods are phase blind as discussed in chapter 2. In order to avoid this limitation, it is shown in [17] that the channel phase information can be extracted from the second-order cyclostationary statistics (SOCS). But oversampling and multichannel configuration (diversity) are required for SOCS based methods, and when a single sensor is used these conditions cannot always be satisfied. Thus, SOCS based methods are not suitable for baud rate spaced systems [56]. On the other hand, higher order statistics (HOS) can be used for NMP channel estimation if the input signal is not Gaussian, as shown in [56] and references therein. But HOS methods have a high computational complexity and difficulty in implementation.

Lii and Rosenblatt [8] have noted that combining SOS with HOS can provide the solution to the blind channel estimation problem. But they did not propose any algorithms. Reference [9] extends this idea by using the full fourth order cumulant to

locate zero positions. The correct location of the zeros can be obtained via the use of various cost functions, which are discussed in detail in this chapter.

In this chapter, a two-step approach is used in the proposed algorithms. In the first step, assuming that the channel is minimum phase, zeros are estimated using a SOS based method. Three methods are used in the second step. They take advantage of the best SOS based estimation method reported in literature [6] and other NMP information to estimate the unknown characteristics of communication channels.

The first method, called SH, utilizes slice of fourth order cumulant with SOS to exploit the NMP channel estimation in section 3.3.1. It has also been noted in the literature that reduced cumulant information derived from a cumulant or a cumulant slice has the capability of selecting correct zero location instead of using the full cumulant [56, 57]. However, a single point of the fourth order cumulant is not robust enough to identify the correct zeros location as shown in [57].

The second method, named SK, utilizes kurtosis (one point of the fourth order cumulant) instead of using the full cumulant or cumulant slice, with the incorporated linear residue zero-forcing equalizer, to estimate unknown channel parameter. The well-known constant modulus algorithm (CMA) [14] notes that the channel input signal has a constant modulus. As an extension of CMA, to achieve equalization, the Shalvi-Weinstein algorithm [13] maximizes the kurtosis subjected to the condition that the power of the equalizer input and output remain equal. In this chapter, we use a simplified version of this criterion such that the normalized kurtosis at the transmitter and the receiver being made to equal. The zero locations are efficiently located using this normalized kurtosis criterion and thus avoids the use of complicated full (or slices of) HOS cumulants. Based on this, the second proposed method (SK) is described in section 3.3.2.

The third method, called SF, employs FA property at the equalizer output. An important property that the transmitted signal only takes values in a finite alphabet set is ignored in most existing blind channel estimation algorithms, such as [17, 58]. The FA property of the transmitted signal has shown to be extremely useful and the use of FA property in channel estimation and equalization has been discussed in recent papers [47-49, 59-61]. Univariate case is studied in [48, 59, 61]. Multivariate and multichannel problems are solved in [47] [60]. FA property is also used in OFDM communication system estimation in [49]. In section 3.3.3, FA property is investigated. The third proposed method (SF) takes advantage of the best SOS based estimation method in conjunction with the FA property of the transmitted signal to estimate the channel parameters and recover the original input signal with the use of the zero-forcing equalizer.

The estimation results obtained by the last two algorithms (SK and SF) can be further improved by a subsequent recursive processing using the inherent finite alphabet property of the transmitted signal. A refined estimation algorithm is then proposed based on such recursion. As noted before, using FA characteristics, the equalizer output signal can be recursively used to improve the initial estimation. The recursive use of the output has similarity to the iterative least squares with enumeration (ILSE) and iterative least squares with projection (ILSP) in [60] which exploit FA property to provide channel parameter and recover original signal. However, the proposed algorithms here (LS-SK, LS-SF) are different to these in that they do not require oversampling (as in the use of an antenna array) and does not have initial value problems as of ILSE and ILSP. Only a single iteration of a least square computation is used in the proposed algorithms. The comparison results show that the

proposed methods achieve better performance than any reported technique. The detail method is shown in section 3.3.4.

The main contribution of this chapter is the proposal and evaluation of three simple, low complexity blind channel estimation techniques (SH, SK & SF), and the refinement of these methods (LS-SK & LS-SF). The performances of the proposed methods are compared in detail in the chapter. As the proposed methods incorporate a simple equalizer, a separate equalizer implementation is unnecessary.

3.2 Channel Model and Initial Zeros estimation

The channel model is same as (2.3) presented in chapter 2, except we do not assume the channel zeros must be inside the unit circle. For a practical wireless communication channel, channel zeros can be minimum or maximum phase, i.e. the magnitude of zero $\{b(k)\}$ can be lesser or larger than unity. It is noted that a zero inside the unit circle ($|b(k)| < 1$) and its reciprocal on the unit circle ($1/|b(k)| > 1$) yield the same autocorrelation sequence [62]. As noted in chapter 2, all the minimum phase zeros can be directly obtained from the autocorrelation polynomial as,

$$(\hat{b}(1), \hat{b}(2), \dots, \hat{b}(L)) = \min_ph \left(roots \left(\sum_i \hat{r}_{yy}(i) z^{-i} \right) \right) \quad (3.1)$$

The operator $\min_ph(\cdot)$ only selects zeros inside the unit circle from the $roots(\cdot)$ operation. Alternatively, the minimum phase zeros can be obtained as,

$$(\hat{b}(1), \hat{b}(2), \dots, \hat{b}(L)) = roots \left(\sum_{k=0}^L \hat{h}(k) z^{-k} \right) \quad (3.2)$$

where parameters $\{\hat{h}(k)\}$ are estimated by any (sophisticated) SOS based methods.

For each MP zero estimated via the SOS based method, we note that there would be an alternative maximum-phase zero [62], and thus using $(\hat{b}(1), \hat{b}(2), \dots, \hat{b}(L))$, a non-

minimum-phase system can be obtained by reciprocating any number of zeros on the unit circle. For an L^{th} order system, there are 2^L such configurations. For example, the zeros can be $\varphi = (\hat{b}(1), 1/\hat{b}^*(2), \dots, \hat{b}(L))$ or $\varphi = (1/\hat{b}^*(1), \hat{b}(2), \dots, \hat{b}(L))$. Here we propose to select the correct configuration by observing the output of the proposed cost functions.

3.3 Proposed Algorithms

3.3.1 SOS and HOS Slice (SH) Based Algorithm

Before proceeding to the proposed algorithms, some basic knowledge of HOS is introduced. If a random process is symmetrically distributed, then its third-order cumulant is zero; hence, the fourth-order cumulant (trispectrum) is needed for estimation [10]. For example, the BPSK, QAM signals are symmetrically distributed. Their corresponding third order cumulants are zero. As such, it is necessary to use the fourth order cumulant in conjunction with the second order cumulant for the channel estimation to utilize both advantages and overcome the drawbacks. The fourth order cumulant of the signal $\{y(n)\}$ is given as,

$$c_{4y}(\tau_1, \tau_2, \tau_3) = E\{y^*(t)y(t+\tau_1)y(t+\tau_2)y^*(t+\tau_3)\} - E\{y(t)y^*(t+\tau_1)\}E\{y(t+\tau_2)y^*(t+\tau_3)\} \\ - E\{y(t)y^*(t+\tau_2)\}E\{y(t+\tau_1)y^*(t+\tau_3)\} - E\{y(t+\tau_1)y^*(t+\tau_2)\}E\{y(t)y^*(t+\tau_3)\} \quad (3.3)$$

And the sample fourth order cumulant can be estimated as,

$$\hat{C}_{4y}(\tau_1, \tau_2, \tau_3) = \frac{1}{N} \sum_{n=1}^{N-k} y^*(n)y(n+\tau_1)y(n+\tau_2)y^*(n+\tau_3) \\ - \hat{r}_{yy}(\tau_1)\hat{r}_{2y}(\tau_2 - \tau_3) - \hat{r}_{yy}(\tau_2)\hat{r}_{2y}(\tau_1 - \tau_3) - \hat{r}_{yy}(\tau_3)\hat{r}_{2y}(\tau_1 - \tau_2) \quad (3.4)$$

where $k = \max(\tau_1, \tau_2, \tau_3)$ and τ_1, τ_2, τ_3 are lag variables of fourth order cumulant. The hypothetical value of the fourth order cumulant of $y(n)$ also can be expressed via the channel impulse response as,

$$C_{4y}(\tau_1, \tau_2, \tau_3) = \gamma_{4x} \sum_{n=0}^{\infty} h^*(n)h(n+\tau_1)h(n+\tau_2)h^*(n+\tau_3) \quad (3.5)$$

where γ_{4x} is the fourth order cumulant of the input signal $\{x(n)\}$, which is given by

$$\gamma_{4x} = C_{4y}(0,0,0) / \sum_{k=0}^q [C_{4y}(q,0,k) / C_{4y}(q,0,0)]^4 \quad (3.6)$$

where γ_{4x} denotes 4th order cumulant of input signal $\{x(n)\}$, and γ_{4x} can be accurately calculated by using the constellation information of the transmitted signal without using the above formula (3.6). From (3.3)-(3.6), higher order cumulants are multidimensional functions. As substantial number of samples is involved, their computation is intensive. The slices of higher order cumulant are used to exploit useful information of non-Gaussian stationary process [63]. We can fix three, two, one or none of the variables in the vector (τ_1, τ_2, τ_3) to obtain different slice. One-dimensional (1D) slice of fourth-order cumulant is obtained by freezing 2 of its 3 lags, such as $\hat{C}_{4y}(\tau_1, 0, 0)$. The two-dimensional (2D) slice of the fourth-order cumulant can be obtained by freezing 1 of its 3 indexes, for example, $\hat{C}_{4y}(\tau_1, \tau_2, 0)$. In analogy, full-slice of the n^{th} order cumulant, i.e. entire cumulant is obtained by not fixing any index. If the fourth order cumulant of the observed signal is equal to the hypothetical fourth order cumulant evaluated using the estimated parameters, then the estimated channel parameters are the correct one. The following cost function [57] is considered for this purpose,

$$\sum_{\tau_1=0}^L \sum_{\tau_2=0}^L \sum_{\tau_3=0}^L \left| \hat{C}_{4y}(\tau_1, \tau_2, \tau_3) - C_{4y}(\tau_1, \tau_2, \tau_3 | \varphi) \right|^2 \quad (3.7)$$

Where φ is the set of estimated zeros. Because the 4th order cumulant is used to select the correct zeros of the system, and the computation of 4th order cumulant is time consuming, efficient method of implementing the proposed method have been investigated. For 2D, the cost function similar to (3.7) is expressed as,

$$\sum_{\tau_1=0}^L \sum_{\tau_2=0}^L \left| \hat{C}_{4,y}(\tau_1, \tau_2, 0) - C_{4,y}(\tau_1, \tau_2, 0 | \varphi) \right|^2 \quad (3.8)$$

The cost function related to 1D slice is:

$$\sum_{\tau_1=0}^L \left| \hat{C}_{4,y}(\tau_1, 0, 0) - C_{4,y}(\tau_1, 0, 0 | \varphi) \right|^2 \quad (3.9)$$

The procedure of the proposed SH method is summarized as,

1. Find initial zeros from estimated channel parameters by SOS method in chapter 2.
2. Using the zeros and their reciprocals, we can obtain 2^L different systems (i.e. by reflecting one or more minimum phase zeros to reciprocal location outside the unit circle). For different φ , a corresponding $\{\hat{h}(k)\}$ can be mapped from one zero set φ . In order to compare with fourth order cumulant, the $\{\hat{h}(k)\}$ should be normalized.
3. From the output data, the estimated value of fourth order cumulant can also be calculated by (3.4).
4. For each system above, we can evaluate possible (hypothesized) values for theoretical fourth order cumulants via (3.5).
5. Comparing the estimated 4th order cumulant with all hypothesized 4th order cumulants, it is possible to choose a set of roots which minimize Euclidean distance in the cumulant domain (3.8) for using 2D slice, or (3.9) for using 1D slice.

Thus the true zeros of the FIR model can be obtained from combining the second order statistics and slice of higher order statistics of the output data, i.e. the parameters of the system are estimated by SH method. In [57], the performances of using one cumulant point, 1D slice, 2D slice and full cumulant are compared. Numerical examples of using the algorithm and the robustness of algorithm are also shown in [57].

The computational complexity of using cumulant slice is lesser than using the full cumulant. And the computational load of one point of 4th order cumulant is lesser than that of any other cumulant slice. The results indicate that the slice of cumulant has the same effect in selecting correct roots as the full cumulant does, however, one point of

the fourth order cumulant is not robust enough to find the correct location of channel zeros [57].

3.3.2 SOS and Kurtosis based Algorithm (SK)

Based on [57] which uses a linear programming approach to find the location of system zeros by cumulant slice, the second proposed algorithm (SK) is presented. In here, it will be shown that one point of fourth order cumulant is robust enough to select the correct roots.

Usually, the equalizer is designed after the channel estimation and the system phase information needs to be known. In the case of adaptive equalizers, the equalizers are made to adapt using the phase information. In the proposed method the phase information of the communication channel is recovered from the equalizer output.

A simple zero-forcing equalizer (see Fig 3.1) based on the zeros estimated in the previous subsection is needed for channel estimation. For the zero-forcing equalizer,

$$C(z^{-1})H(z^{-1}) = 1 \quad (3.10)$$

The inverse filter (equalizer) with L poles can be expressed in a cascade form,

$$C(z^{-1}) = \frac{1}{H(z^{-1})} = \prod_{k=1}^L H_k^B(z^{-1}) \quad (3.11)$$

where $H_k^B(z^{-1})$ is a branch transfer function corresponding to each zero $b(k)$. The detail of the equalizer implementation is addressed in chapter 5.

The proposed zero-forcing equalizer has low computation load because we only need to realize branches $2 \times L$ for 2^L different configurations stated above. Furthermore, a recursive architecture based equalizer that has efficiency in hardware implementation is proposed in [46].

Figure 3.1 Zero-Forcing equalizer for SISO channel

As shown in Fig. 3.1, the equalizer output signal $s(n)$ can be expressed as,

$$s(n) = x(n) * h(n) * c(n) + w(n) * c(n) \quad (3.12)$$

(3.12) can be rewritten as $s(n) = x(n) * g(n) + c(n) * w(n)$. Where $\{c(n)\}$ are the impulse response of the equalizer. It is noted in [14] that the output of the inverse filter has the same probability distribution information as the input signal's. Suppose that the vector $g(n) = h(n) * c(n) = (g_1, g_2, \dots)$ is denoted as $\mathbf{g}$. The sufficient condition to achieve equalization is that $\mathbf{g}$ should be a unit vector having only one nonzero component equal to the phase shift [13]. As a further simplification of this condition, here we propose to use the kurtosis of the transmitted signal for equalization. Kurtosis is the fourth order cumulant of the signal at zero lags. (Note for brevity, we use x_n for $x(n)$, s_n for $s(n)$, w_n for $w(n)$ in the following deduction.) The kurtosis of the equalizer output s_n is

$$K(s_n) = Cum_{4s} = E\{|s_n|^4\} - 2E^2\{|s_n|^2\} - |E\{s_n^2\}|^2 \quad (3.13)$$

A similar form exists for the input signal x_n . Using the i.i.d assumption on the input signal x_n , we get

$$K(s_n) = K(x_n) \sum_l |g_l|^4 + K(w_n) \sum_l |c_l|^4 \quad (3.14)$$

$$E(|s_n|^2) = E(|x_n|^2) \sum_l |g_l|^2 + E(|w_n|^2) \sum_l |c_l|^2 \quad (3.15)$$

Note that $K(w_n) = 0$ as the kurtosis of a Gaussian signal is zero. After simplification, the relationship between the normalized kurtosis of s_n and x_n in (3.13) can be expressed as,

$$\frac{K(x_n)}{E^2\{|x_n|^2\}} - \frac{K(s_n)}{E^2\{|s_n|^2\}} - \frac{K(s_n)}{E^2\{|s_n|^2\}} \frac{\phi^2 + 2\phi\theta}{(\phi + \theta)^2} = \frac{K(x_n)}{E^2\{|x_n|^2\}} \left| 1 - \frac{\sum |g_l|^4}{(\sum |g_l|^2)^2} \right| \frac{\theta}{(\phi + \theta)^2} \quad (3.16)$$

where $\phi = E\{|w_n|^2\} \sum_l |c_l|^2$ a constant, that depends on the noise power and $\theta = E\{|x_n|^2\} \sum_l |g_l|^2$ is a constant because the equalizer impulse responses $\{c_l\}$ are chosen to have the same autocorrelation function for different configurations. Therefore, the minimization of left side of (3.16) is the minimization of $\left| 1 - \sum_l |g_l|^4 / (\sum_l |g_l|^2)^2 \right|$. Note that for the vector $\mathbf{g}$, (3.16) is minimized if and only if $\mathbf{g}$ has at most one nonzero component, $\left| \sum_l |g_l|^4 = (\sum_l |g_l|^2)^2 \right|$, i.e., $\mathbf{g}$ is a proper equalizer transfer function. As the constellation of transmitted (e.g. communication) signal is known, based on (3.16), a cost function can be devised as the criterion for equalization which is given by

$$J(\varphi) = \left| \frac{K(x_n)}{E^2\{|x_n|^2\}} - \frac{K(s_n | \varphi)}{E^2\{|s_n | \varphi|^2\}} - \xi \right| \quad (3.17)$$

This makes the equalization easier and simpler when compared with, for example the use of Shavli-Weinstein criterion in [13]. In equation (3.17) the constant ξ can be evaluated once the signal to noise ratio is known. The offset ξ in (3.17) can be ignored if the SNR is high. We note that $J(\varphi)$ has following properties: nonnegative; $J(\varphi) \geq 0$, and $J(\varphi)$ is minimized if and only if the input normalized kurtosis is closest to the normalized output kurtosis. That means when the constellation of the equalizer output is similar to the constellation of the input signal, i.e. correct

equalization. Thus, using the kurtosis, the mixed-phase channel zeros, which were initially estimated by an SOS based method can be correctly located.

The procedure of the algorithm based on the discussed cost function can be summarized as,

1. Find initial zeros from estimated channel parameters by SOS method
2. Zero-forcing equalizer is constructed via using one configuration of zeros from 2^L combinations.
3. Given equalizer output, calculate the cost function (3.17).
4. Repeat the step 2. Correct zeros belong to the configuration that minimizes the 2^L results.
5. Evaluate the channel parameters based on the estimated zeros.

3.3.3 SOS and FA Property based Algorithm (SF)

It is known that the transmitted signal in communication channel only appertains to a finite alphabet set Ω . $\{x(i)\} \in \Omega$. For example, BPSK signal symbol occurs at +1 or -1 with $\Omega = \{+1, -1\}$. And $\Omega = \{\pm 1, \pm 3, \dots, \pm i\} \oplus \{\pm 1, \pm 3, \dots, \pm i\}$ for QAM signals. If m is the length of the set Ω , $m = 2$ for BPSK signal. The ideal equalizer output signal can be expressed as $s(n) = \alpha x(n - \tau)$ where α is the amplitude gain and integer τ denotes time delay. A properly equalized output symbols have the same FA characteristics as those of the input symbols. In this section, the cost function exploiting the FA property at equalizer output is discussed. The performance of this cost function is compared with known efficient techniques in [48, 61] exploring FA property in choosing correct zeros.

In order to determine the deviation of the equalizer output from the original input sequence, a cost function based on the FA property is proposed as,

$$J(\varphi) = E\{(s_n | \varphi - \Omega_k)^2\} = \frac{1}{N} \sum_{n=1}^N (s_n | \varphi - \Omega_k)^2 \quad (3.18)$$

where N is the number of data samples, and Ω_k is the k th number of FA set Ω . $J(\varphi)$ is a cost function that will approximate to zero when all the equalizer output $\{s(n)\}$

are close to the corresponding symbols in FA set. Any deviation will increase the summation. $J(\varphi)$ has following properties: nonnegative; $J(\varphi) \geq 0$, and $J(\varphi)$ is minimized if and only if φ is the channel FIR filter and $1/\varphi$ is the correct equalizer. The procedure of the algorithm SF is the same as that of SK algorithm except for the use of the cost function in (3.18) instead of the one in (3.17).

To evaluate the performance of the proposed SF method, we have also used Li's cost function [48, 61] for comparison.

$$J(\varphi) = E \left\{ \prod_{k=1}^m (s_n | \varphi - \Omega_k)^2 \right\} = \frac{1}{N} \sum_{n=1}^N \prod_{k=1}^m (s_n | \varphi - \Omega_k)^2 \quad (3.19)$$

$J(\varphi)$ is constructed from a series of multiplications that will approximate to zero when equalizer output $\{s(n)\}$ is close to any symbols in the FA set. It has the same properties as the cost function in (3.18): nonnegative; $J(\varphi) \geq 0$, and $J(\varphi)$ is minimized if and only if φ is the channel FIR filter and $1/\varphi$ is the correct equalizer. For example, if the input signal is BPSK signal, (3.19) can be expressed as,

$$J(\varphi) = \frac{1}{N} \sum_{n=1}^N (s_n | \varphi - 1)^2 (s_n | \varphi - (-1))^2$$

One of the main limitations of Li's cost function is that all the symbols of FA set are used for one sample of computation to determine the deviation of the equalizer output from the original input sequence. To minimize (3.19), a complex gradient search algorithm can be used to find the system parameters as in [48, 61]. In order to obtain the global minimum value, the constraint such as $\sum h(n) = 1$ or $\sum |h(n)|^2 = 1$ is imposed. Here in the proposed SF method the complex searching approach is not necessary and correct zeros' locations are found from those 2^L combinations by minimizing (3.18), and a global minimum value is always guaranteed. By far, the proposed SF method here is more efficient in using the FA property of the transmitted

signal than the use of (3.19). This is mainly due to the fact that every observed sample at equalizer output is only compared with the closest symbol of the FA set.

3.3.4 Performance Improved by Least Square Method (LS-SK & LS-SF)

Figure 3.2 Structure of refined recursive estimator

It is noted that the equalizer output $\{s(n)\}$ can be used recursively to provide a better estimation as shown in Fig. 3.2. For this, we project every data $\{s(n)\}$ to the closest FA symbol set, to obtain $\{v(n)\}$. Combination of $\{v(n)\}$ and the observed noisy signal $\{y(n)\}$ would then provide the coefficients $\{\hat{h}(k)\}$ of the unknown system. To do this, replace $\{x(n)\}$ by the equalizer output $\{v(n)\}$ in (2.3), to solve $y = v * \hat{h} + \varepsilon$. In order to estimate the parameters $\{\hat{h}(k)\}$, the estimation error ε can be minimized in a least square sense to obtain a minimization problem,

$$\sum_{i=1}^n \|Y - V\hat{h}\|^2 \quad (3.20)$$

which can be solved for the parameters $\{\hat{h}(k)\}$ by,

$$\hat{h} = (V^T V)^{-1} V^T Y \quad (3.21)$$

where $\hat{h} = [\hat{h}_0, \hat{h}_1, \dots, \hat{h}_L]^T$, $Y = [y(n_1), y(n_1 + 1), \dots, y(n_2)]^T$, $V = [v_{n_1}, v_{n_1+1}, \dots, v_{n_2}]^T$, and $v_i = [v(i + L), v(i + L - 1), \dots, v(0)]$. With known $\{v(n)\}$ and $\{y(n)\}$, the coefficients $\{\hat{h}(k)\}$ can be obtained, and usually, $n_2 - n_1 = 10 * L$, is sufficient to

provide a highly accurate estimate. By not using all the samples, the computational complexity of the LS method can be reduced.

3.4 Performance Evaluation and Comparison

To demonstrate the performance of the proposed methods (SK, SF, LS-SK and LS-SF), several simulation examples are presented in this section. Three different channels are used in these examples.

Channel I: This is a widely cited channel and has been used in [56] and references therein. The system transfer function of this 3rd order NMP model is $H(z^{-1}) = 1 - 0.9z^{-1} + 0.385z^{-2} + 0.771z^{-3}$ having system zeros at 0.6 and $0.75 \pm j0.85$.

Channel II: A second order MP system having zeros at 0.5 and 0.3. The system transfer function is $H(z^{-1}) = 1 - 0.8z^{-1} + 0.15z^{-2}$.

Channel III: This channel, a second order MP model having system zeros at $0.7 \pm j0.7$, is also used in [56] and references therein. The system transfer function is $H(z^{-1}) = 1 - 1.4z^{-1} + 0.98z^{-2}$. The channel zeros have magnitude of 0.9899 and thus are extremely close to the unit circle.

In these examples, the channel input signals are selected as i.i.d. QPSK sequences having zero mean. The additive channel noise is modeled as complex white Gaussian processes with zero-mean and independent to the channel input. The SNR (Signal to Noise Ratio) is defined as $SNR = 10 \log_{10}(P_{y_s} / P_w)$ (dB) where P_{y_s} denotes the power of channel output signal y_s and P_w is the additive noise power. The estimation accuracy is evaluated in NMSE.

3.4.1. Sensitivity to the Cost Functions

In section 3.4, we have discussed three cost functions via equations (3.17), (3.18) and (3.19). SK method uses the cost function in (3.17) while SF method uses the cost

function in (3.18). The SF method can also be implemented using Li's cost function as defined in (3.19). NMSE performances of the use of the three cost functions are shown in Fig. 3.3. Results from the use of Li's method are also shown. The results of Fig. 3.3 show that the proposed SK method and SF method have very similar performances and have advantage over the use of Li's cost function. Furthermore, the least squares methods (LS-SK and LS-SF) improve the estimation accuracy dramatically, as the FA property provides extra information besides the use of SOS and HOS information. It is noted that the least-squares method is one of the best methods to estimate a given set of parameters by minimizing the sum of the squares appearing in (3.21).

It can be concluded from Fig.3.3 that the kurtosis and FA property have the same selectivity in locating the correct zeros, thus performing equally well as a criterion for blind communication channel equalization. This is not surprising as the kurtosis is fundamentally related to FA characteristics. However, when the constellation becomes denser, the use of kurtosis loses its strength as it approaches a Gaussian kurtosis. The use of FA property, on the other hand, is not sensitive to the constellation density.

Figure 3.3 Performance comparison of the proposed methods with Li's cost function. Channel I. 1000 Monte Carlo Runs, $N=2048$ for each Run.

3.4.2. Sensitivity to SOS Methods

It can be seen from Fig. 3.2 that the preliminary step in equalization is the SOS method. Thus, the performance of the proposed SF and SK methods naturally depends on the used SOS methods. Since SK/SF methods and LS-SK/LS-SF methods have similar performance only the performance of SK and LS-SK methods are considered here. Three simulation results based on ACF (autocorrelation function), Durbin method and OS method are shown in Fig. 3.4, for the NMP channel I. The performance of the proposed LS-SK (LS-SF) algorithm based on the three different SOS methods is very close especially when SNR is high. Thus we can see that the LS-SK (or LS-SF) methods are reasonably independent of the used SOS method.

Figure 3.4 Performance comparison of proposed methods based on different SOS methods. Channel I.

1000 Monte Carlo Runs, $N=2048$ for each Run.

3.4.3. Comparison with HOS Technique-GEWS

The GEWS algorithm via the use of HOS slices for FIR channel estimation has been proposed in [56]. GEWS is used for comparison since it is arguably the best and the most recent HOS technique reported in the literature. The comparison results are shown in Fig. 3.5. The proposed SK/SF algorithms using OS method (for SOS) have better performance than GEWS algorithm. The LS-SK method using ACF or OS method outperforms the GEWS algorithm and converges to a very low value rapidly and shows the best performance.

Figure 3.5 Performance comparison of GEWS with the proposed SK and LS-SK algorithms based on OS method and ACF method. Channel I. N=800 for each run, 200 Runs.

In Fig. 3.6, the performance of proposed methods is shown for different sample data lengths. The data length used for estimation varies from 100 to 3200 samples. Channel III is used in the simulation. 200 runs are executed. SNR is equal to 20dB. As the zeros of channel III are very close to unit circle, this special case is an example of a severe fading channel. The proposed LS-SK method with the OS algorithm outperforms the GEWS algorithm and has better performance.

Figure 3.6 Performance comparison of GEWS with the proposed SK and LS-SK methods based on different SOS methods for different number of samples.

However, using ACF as initial zero estimation does not provide good performance since the system zeros are too close to the unit circle. Furthermore, if the channel roots are not very close to the unit circle (if fading is not severe in the communication channel), any simple SOS based method, such as ACF, can be used in the algorithm to obtain an extremely low complexity equalizer (for example, results in Fig. 3.3—Fig.3.6).

3.4.4. Symbol Error Rate (SER) Performance

It is noted that the symbol error rate is the final test for communication performance evaluation, and that the equalizer output noise variance is directly related to the symbol error rate via the complementary error function. (The noise is assumed to have a Gaussian probability density function) [64]. More specifically, the probability of symbol error is related to SNR at the equalizer output in the following manner.

$$P_{SER} = \log_2(M)Q(\sqrt{SNR_{EqualizerOP}}) \quad (3.23)$$

where M is the size of the input alphabet. M=4 for QPSK signal. One would define the equalizer output noise variance as ,

$$SNR_{EqualizerOP} = \text{var}(s_n - x_n) \quad (3.24)$$

Therefore, we can use the equalizer output noise variance as a criterion to evaluate the estimation performance. The estimated equalizer output noise variances of the proposed estimators are shown in Fig. 3.7. For comparison, Fig. 3.7 also shows the noise variance estimated assuming that the equalizer is designed using ideal channel parameters.

Figure 3.7 The noise variance performance of the SK method, LS-SK method and ideal channel.

Channel I. N=2048 for Each Run. 1000 Runs.

From Fig. 3.8, for channel III, it can be seen that the equalizer output noise variance obtained using the estimated parameters of the proposed LS-SK method is close to the noise variance resulting from a perfectly estimated channel. The difference between LS-SK and SK is also clear from Fig. 3.8. The equalizer output noise variance can be used to determine the SER through (3.23). This is shown in Fig. 3.8(a). In order to justify that the noise variance can be considered as an evaluation criterion for the equalizer, the SER has been evaluated by simulating 100 symbol errors at the equalizer output. The number of samples in each run is 2048. The input signal is QPSK signal. This is shown in Fig. 3.8(b). Since the result in Fig. 3.7 is consistent with that of Fig. 3.8, we state that by evaluating the equalizer output noise variance, one can clearly predict the SER performances. Actual simulation of SER is extremely computationally intensive, especially when the SNR is larger than 20dB.

(a)

(b)

Figure 3.8 (a) SER performance evaluation using the equalizer output noise variance. (b) SER performance evaluated by simulating symbol errors at the output.

3.4.5 Application in Wireless Communication Channels

Channel IV: a two-ray multipath mobile radio channel with duration of six symbols [33]. The continuous time channel $h(t)$ for $t \in [0, 6T)$ is expressed as,

$h(t) = e^{-j2\pi(0.15)} r_c(t - 0.25T, \beta) + e^{-j2\pi(0.6)} r_c(t - T, \beta)$. The function $r_c(t, \beta)$ is raised

cosine function, β is roll off factor and $\beta = 0.35$. The discrete time channel $h(n)$ is sampled by $h(n)=h(nT)$ for $n=0, 1, \dots, 5$. We get the coefficients of channel IV as $h = \{0.5254 - 0.7232i, -0.4819 + 0.2427i, -0.0523 + 0.0719i, 0.0177 - 0.0243i, -0.0033 + 0.0046i, -0.0014 + 0.0019i\}$. We consider the example (Channel IV) used by G.B. Giannakis in [33]. The estimation results of proposed methods are shown in Fig. 3.9. Based on the correct zero-configuration found by SK method, the LS-SK method achieves the best performance. In this example, we can see that the proposed methods work for longer channel and the difference between SK and SF. SK is better than SF in the long channel estimation.

Figure 3.9 Channel IV. BPSK is the input signal. 1000 runs. 1024 samples are used in each run. The SNR varies from 10dB to 30dB.

Another complex communication channel under investigation is given by impulse response of $h = [2 - 0.4i \ 1.5 + 1.8i \ 11.2 - 1.3i \ 0.8 + 1.6i]$. It is used in Labat and Macchi's paper and reference therein. The performance of LS-SK in this channel is shown in Fig. 3.10.

Figure 3.10 BPSK is the input signal. 1000 runs. 1024 samples are used in each run. The SNR varies from 5dB to 50dB.

3.4.6 Channel Tracking Performance

In this section, we consider a slowly time varying channel. The transfer function of the time-varying channel is:

$$H(z^{-1}) = (0.334 + a_0) + (0.3006 + a_1)z^{-1} + (0.1286 + a_2)z^{-2} + (-0.2573 + a_3)z^{-3} .$$

The time-varying coefficients (a_0, a_1, a_2, a_3) are obtained from a color Gaussian noise sequence which driven by a Butterworth filter with standard deviation $\beta = 0.1$ respectively as described in [65]. The channel coefficients are estimated using 1024 sample. Within this period the coefficients are assumed to be constant. Initially, the channel is estimated using the SK method. In the subsequent estimation, only the SOS information in used and the channel coefficients are tracked to determine the correct zero locations. Thus the selection over 2^L configurations is not necessary. The tracking results are shown in Fig. 3.11.

In Fig. 3.11, the estimated coefficients are shown together with the original coefficients. Simulations show that coefficient-tracking is possible when channel

variations are not very large. However, a detailed investigation of the tracking is not presented here.

Figure 3.11 The tracking performance of the proposal. SNR=20dB. The original channel impulses are plotted in solid line. The estimated parameters are plotted in symbols. The input signal is BPSK.

3.5 Training Estimation

We note that if a training sequence is used for channel estimation, the estimation error of least squares technique used for training estimation can be expressed as,

$$NMSE_{TS} = \sum_{k=0}^L |h(k) - \hat{h}(k)|^2 / \sum_{i=0}^L |h(k)|^2 = P_w / (P_{ys} N) \quad (3.25)$$

and one could use this as a bench-mark for evaluation of estimation performance. The channel I in this chapter is used for simulation with 800 samples in each run. Results are shown in Fig. 3.12. The proposed SK, LS-SK methods, HOS based algorithm GEWS, and the NMP coefficient estimation bound in Appendix B are compared with the training estimation. The use of recursive estimation via LS converges to a very low value rapidly and approach the estimation accuracy of a training sequence. The discrepancy between the training sequence and proposed recursive algorithm could be accounted for the symbol errors resulting in the estimation, as noted in equation

(3.25). Further more, simulations have shown that another recursion on LS would achieve NMSE as same as that of using a training sequence.

Figure 3.12 Performance comparison of the proposed method with GEWS and the use of training sequences. $N = 800$, and 200 Monte Carlo iterations

3.6 Performance with Estimated Channel Order

In practical situations, the unknown channel order needs to be estimated. In this section, the robustness of proposed method LS-SK for order estimation errors is noted and the results are shown in Fig. 3.13. Simulations show that the overestimated channel order has little impact on the equalization performance. Underestimated channel order impacts the estimation performance in MSE largely. The channel used in the simulations is the third order Channel I, and the estimated channel order is varying from 2 to 6. Input signal is QPSK, the SNR is 20dB, and 100 iterations are simulated with 1024 samples in each iteration.

Figure 3.13 Mean square error variation with estimated channel order. Correct channel order=3.

3.7 Summary

In this chapter, three algorithms for blind NMP FIR channel coefficients estimation are proposed. The first method is using slices of fourth order cumulant to solve the zeros location. It has lower computational load than the existing algorithm which use full cumulant to solve where is the channel zero. Via the use of a zero-forcing equalizer, two other novel blind FIR channel parameter estimation techniques are proposed. They take advantage of the existing, most efficient SOS based methods in conjunction with the kurtosis or the finite alphabet property of the transmitted signal. The methods also provides good performance when the channel zeros are close to unit circle. The equalizer output is used once recursively to achieve a very low estimation error. Simulation results demonstrate the superiority of the proposed algorithms. It has been shown that at a low number of data samples, the proposed methods are superior to any reported HOS techniques. This is not surprising as HOS techniques need larger data samples (or low noise) to achieve better performances. As the proposed methods

inherently use an equalizer, separate equalizer design is not required, thus making the method attractive in hardware realization. Note that if channel zeros are close to the unit circle, linear equalizers would not result in proper equalization, other efficient recursive equalizer architectures as discussed in chapter 5 are required.

The choice of the order of the communication channel is an important design step. If this order is estimated to be too small, under determination of channel order can cause deterioration in equalizer performance. As recursive least squares estimation affects the ultimate estimation performance, the under determination of channel order will deteriorate the estimation performance. Simulation shows that the over order-determination has little impact to the estimation performance. As the over estimated parameters are comparatively small or can be thought of small coefficients. The over estimated parameters have little impact to the equalizer performance as well. So the recursive least squares method can still provide satisfying results.

Chapter 4

Blind Single Input Multiple Output Channel Parameter Estimation

As a succession of the algorithms in chapter 3, joint blind channel estimation and equalization techniques for single input multiple output (SIMO) channels are under investigation in this chapter. It is noted that the polynomial correlation matrix (PCM) of SIMO channel model, whose elements are the Z-transform of the output cross-correlation sequences, contains channel phase and amplitude information. Under low noise environments, the PCM can be elegantly used for channel estimation. In order to use the PCM matrix more robustly in noisy environments, in this chapter, we propose two step procedures for SIMO channel estimation and equalization. In the first step, strongest sub-channel is estimated using the SK method proposed in chapter 3. In the second step, the estimates are refined via the use of SIMO channel diversity. In this second step, if the finite alphabet property of the transmitted signal is exploited, the estimation results would approach the performance of training estimation. The

proposed techniques are useful in blind channel estimation even in the presence of common zeros among the subchannels.

4.1 Introduction

In high-speed data communications, the SISO channel model can not fulfill the requirements of the emerging new application requirements. It is noted that single-input multiple-output (SIMO) transmission is widely used, as it uses channel diversity to improve the communication performance, particular in severely fading channels. SIMO channel estimation and equalization have applications in diverse scientific and engineering areas, such as wireless communication, image de-blurring, television broadcasting [21]. A large number of techniques for the blind SIMO channel estimation has been proposed since the appearance of [16]. One can refer to [21] for details of these methods. Also subsequent SIMO equalization based on the estimated channel impulse response can be found in [16, 18, 30]. Thus SIMO channel estimation plays an important role in communications. In this chapter, simple but efficient techniques for joint SIMO channel estimation and equalization are proposed.

Note that the second order cyclostationary statistics (SOCS), an SOS based technique, can be used in the non-minimum phase SIMO channel estimation. It is well-known that the primary assumption of the SOCS based methods of having no common zeros in subchannels [21], which obstructs its widely applications. Alternative techniques for SIMO channel estimation can be developed based on higher order statistics (HOS). In [30], a fractionally sampling technique using HOS based technique is proposed for SIMO channel estimation and equalization. Each subchannel parameters are estimated independently by matching the second order cumulant and the fourth order cumulant. Subsequently, all the estimated subchannels

are aligned and scaled to form the actual SIMO channels. However, the use of HOS is not as accurate as the use of SOCS in SIMO channel estimation and the computational load of HOS is comparatively higher. If SOS is used to obtain the amplitude information of the unknown channel and channel phase information is estimated by other techniques, the unknown channel can be estimated without using SOCS and HOS to achieve a higher estimation performance. For example, as reported in [54], a parametric method using minimum phase channel zeros estimated by an SOS based method in conjunction with the finite alphabet (FA) property provides a very accurate single input single output (SISO) channel estimation. The work reported here can be considered as an extension of our work in [54] (as in chapter 3) for the case of SIMO channel estimation.

In the proposed methods of this chapter, the first step is to blindly estimate the coefficients of subchannels, independently from the other subchannels, using SISO estimation techniques. Via combining efficient SOS based method with kurtosis property of the equalizer outputs, the subchannels can be estimated with a high accuracy and a lower computational load. For further reduction in computations, only the strongest subchannel needs to be estimated, because the strongest subchannel estimation determines the over-all SIMO channel estimation performance. Subsequently, the polynomial correlation matrix (PCM) of the SIMO model is exploited. PCM is comprised of polynomials, which are the Z-transform of the output cross-correlation sequences. When a large number of samples are available and the additive noise power is low, the PCM can be efficiently used in SIMO channel estimation with a low computational complexity. Also with the use of PCM, having common zeros among subchannels does not pose any problems in estimation. However, when a small number of samples are available and/or a higher noise power

is present, the performance of the use of PCM rapidly deteriorates. In order to overcome this difficulty, a least squares technique is used for SIMO channel estimation via the PCM. As a further improvement, it is also shown how the equalizer output resulting from the strongest subchannel can be used to estimate the other subchannels, via the use of least squares technique.

The SIMO channel estimation in the first step can be further refined by using a recursive process in a subsequent second step. In doing this, the advantage of channel diversity in SIMO channel is utilized. The performance of the proposed method is compared and shown to be better than the existing methods, such as the subspace technique [18], and the GCD (greatest common divisor) technique [66] for SIMO channel estimation, while having a lower computational load. It is also noted here that in communication channels, the transmitted signal only takes values in a finite alphabet (FA) set. The use of the FA property in SIMO channel estimation and equalization has been discussed in some recent papers, such as in [60]. The proposed second step of recursive estimation can be further improved using the FA property. In this method a single iteration of a least squares computation is used, which is a simpler technique than iterative least squares with projection (ILSP) in [60]. It is shown that when the FA information is used, the proposed low complexity technique results in channel estimation as accurate as that could be obtained via the use of training sequences [67]. The use of second order statistics and kurtosis in conjunction with the FA property for blind SIMO channel estimation and the subsequent algorithm performance improvement are the novel contributions reported in this chapter.

The chapter is organized as follows: channel model and assumptions are presented in section 4.2. Section 4.3 discusses the estimation via the use of polynomial

correlation matrix. In section 4.4, the estimation of the strongest subchannel is discussed. Estimation of remaining subchannels is described in section 4.5, followed by discussions of diversity combination and refined estimation in section 4.6. In section 4.7, simulation results under a variety of channel conditions are presented to demonstrate the effectiveness of the proposed methods.

Figure 4.1 SIMO channel model

4.2 Channel Model and Assumptions

We consider the case of having M sub-channels that are resulting from multiple sensors' output sampling at the symbol rate, or resulting from the oversampling of a single sensor output at the receiver. The discrete-time received signal of the m^{th} subchannel at the n^{th} sampling time can be expressed as,

$$y_m(n) = \sum_k h_m(k)x(n-k) + w_m(n) \quad \text{For } m=1,2,\dots,M \quad n=1, 2, \dots, N \quad (4.1)$$

Let $h_m = [h_m(0), h_m(1), \dots, h_m(L)]$ denote the finite impulse response (FIR) of the m^{th} subchannel. The equivalent channel h_m is the convolution result of the transmit filter, the analog channel and the matched filter [11]. Let $\mathbf{h} = [h_1, h_2, \dots, h_M]$ be the collection of entire SIMO channel impulse responses. The block diagram of the SIMO

channel model is illustrated in Fig. 4.1. Let $H_m(z^{-1})$ represent the Z-transform of the subchannel impulse response h_m given by,

$$H_m(z^{-1}) = \sum_{k=0}^L h_m(k) z^{-k} \quad (4.2)$$

And let $b_m(k)$ be the k^{th} zero of the m^{th} subchannel. Z-transform of the FIR channel in (4.2) can be expressed in a cascade multiplication form using first order polynomials as,

$$H_m(z^{-1}) = \prod_{k=1}^L (1 - b_m(k) z^{-1}) \quad (4.3)$$

In the vector notation, the SIMO channel can be rewritten as,

$$\mathbf{Y} = \mathbf{X}\mathbf{H} + \mathbf{W} \quad (4.4)$$

Where matrix $\mathbf{Y}$ is defined as, $\mathbf{Y} = [\mathbf{y}_1^T \mathbf{y}_2^T \cdots \mathbf{y}_M^T]$ with $\mathbf{y}_m = [y_m(1) y_m(2) \cdots y_m(N)]$ and $\mathbf{W}$ is defined in the same form as $\mathbf{Y}$. The whole matrix $\mathbf{Y}$ contains the channel phase information, so permutation of $\mathbf{Y}$ is used to obtain the channel information. The structure in (4.4) is very useful in describing the subsequent least squares technique. For the reasons of convenience, the $N \times (L+1)$ matrix $\mathbf{X}$ containing the data samples is defined as,

$$\mathbf{X} = \begin{pmatrix} x(1) & x(0) & \cdots & x(1-L) \\ x(2) & x(1) & \cdots & x(2-L) \\ \vdots & & \ddots & \vdots \\ x(N) & x(N-1) & \cdots & x(N-L) \end{pmatrix},$$

and the $((L+1) \times M)$ channel coefficients matrix $\mathbf{H} = [h_1^T h_2^T \cdots h_M^T]$ is given by,

$$\mathbf{H} = \begin{pmatrix} h_1(0) & h_2(0) & \cdots & h_M(0) \\ h_1(1) & \ddots & & \vdots \\ & & \ddots & \vdots \\ h_1(L) & h_2(L) & \cdots & h_M(L) \end{pmatrix}$$

Before further discussion, the following assumptions are made on the SIMO channel model in Fig 4.1.

A1) The memory of the channel impulse responses is finite, so that all channels can be modeled as finite impulse response (FIR) filters. All subchannel impulse responses are assumed to be of order L at most. Without loss of generality, it is assumed that $h_m(n) = 0$ for $n < 0$ and $n > L$, and $h_m(0) \neq 0, h_m(L) \neq 0$.

A2) The non-Gaussian stationary transmitted symbols $\{x(n)\}$ are resulting from an independent identical distributed (i.i.d.) process with zero mean. The additive noise signals $\{w_m(n)\}$ $m=1,2,\dots,M$, which are independent of $\{x(n)\}$, are zero mean Gaussian processes with variance (power) σ_w^2 .

A3) The transmitted symbols are from a finite alphabet (FA) set Ω and the constellation information of the FA set is known at the receiver.

A4) No zero of a subchannel appears on the unit circle.

Since the channel impulse response of the SIMO channel $\mathbf{H}$ is unknown, it is necessary to estimate it at the receiver, via methods such as the use of a training sequence or a blind estimation technique. Given the data $\{\mathbf{y}_m \quad 1 \leq m \leq M\}$, in the following we investigate methods for estimating $\mathbf{H}$, without knowing the transmitted symbols $\{x(n)\}$ a prior.

4.3 Blind Channel Estimation from the Polynomial Correlation Matrix

In this section, we consider the correlation sequence of the observed signal $\{\mathbf{y}_m(n)\}$ in (4.4). The two-sided z-transform of the second order cross-correlation sequence of $\{\mathbf{y}_i(n)\} \{\mathbf{y}_j(n)\}$, $1 \leq i \leq M, 1 \leq j \leq M$ can be expressed as,

$$R_{ij}(z^{-1}) = \sum_{l=-L}^L r_{ij}(l) z^{-l} \quad (4.5)$$

And $\{r_{ij}(l)\}$ is the second order cross-correlation sequence given by,

$$r_{ij}(l) = E\{y_i(k)y_j^*(k+l)\} = \sigma_x^2 \sum_k h_i(k)h_j^*(k+l) + \sigma_w^2 \delta(i-j) \quad l = 0, \pm 1, \pm 2, \dots \pm L \quad (4.6)$$

Under assumptions of input signal noted in section 4.2, (4.5) can be expressed using the channel transfer function as [68],

$$\begin{aligned} R_{ij}(z^{-1}) &= \sigma_x^2 H_i(z^{-1})H_j^*(1/z^*) + \sigma_w^2 \delta(i-j) \\ &= \sigma_x^2 \prod_{l=1}^L (1 - b_i(l)z^{-1}) \prod_{l=1}^L (1 - 1/b_j^*(l)z) + \sigma_w^2 \delta(i-j) \end{aligned} \quad (4.7)$$

Assuming low noise power, channel zeros can be estimated using (4.7) as,

$$\text{roots}(R_{ij}(z^{-1})) = [b_i(1), b_i(2), \dots, b_i(L), 1/b_j^*(1), 1/b_j^*(2), \dots, 1/b_j^*(L)] \quad (4.8)$$

It is seen from (4.8) that the information on minimum phase zeros and maximum phase zeros are contained in correlation polynomials. Under low noise power conditions and the availability of sufficient data samples, the estimation of second order correlation sequences can be obtained very accurately. Therefore, the channel zeros and their reflections on the unit circle can be accurately estimated from correlation polynomials. However, as noted earlier, the second order statistics is phase blind in that equation (4.8) alone does not provide information about actual channel zero location, i.e. inside or outside of the unit circle. If the channel is known to be minimum phase channel, then by mapping the minimum phase zeros obtained from (4.8) into the polynomial coefficients, the unknown channel coefficients can be estimated. Similarly, an all maximum phase channel can also be estimated. However, for a mixed phase channel, which is the most common case in communication channels, the locations of channel zeros are unknown. Determination of correct zero locations will be discussed in subsequent section 4.4.

Using (4.5)-(4.8), the polynomial correlation matrix (PCM) of the SIMO channel can be expressed as,

$$\mathbf{R}(z^{-1}) = \begin{bmatrix} R_{11}(z^{-1}) & R_{12}(z^{-1}) & \cdots & R_{1M}(z^{-1}) \\ R_{21}(z^{-1}) & R_{22}(z^{-1}) & & \\ \vdots & & \ddots & \vdots \\ R_{M1}(z^{-1}) & & \cdots & R_{MM}(z^{-1}) \end{bmatrix} \quad (4.9)$$

The matrix $\mathbf{R}(z^{-1})$ is a polynomial matrix with $M \times M$ polynomial elements. Polynomial matrix is deduced from the covariance matrix $\mathbf{Y}$ based on equations of (4.5)–(4.7). So polynomial also contains channel phase information obviously as shown in (4.10)–(4.12). Ignoring the effect of additive noise and by substituting (4.7) into (4.9), it can be seen that the polynomial matrix has a common factor in each row or each column. That is $\mathbf{R}(z^{-1})$ can be rewritten in the following form,

$$\mathbf{R}(z^{-1}) = \begin{bmatrix} \sigma_x^2 H_1(z^{-1}) H_1^*(z) & \sigma_x^2 H_1(z^{-1}) H_2^*(z) & \cdots & \sigma_x^2 H_1(z^{-1}) H_M^*(z) \\ \sigma_x^2 H_2(z^{-1}) H_1^*(z) & \vdots & & \sigma_x^2 H_2(z^{-1}) H_M^*(z) \\ \vdots & & \ddots & \vdots \\ \sigma_x^2 H_M(z^{-1}) H_1^*(z) & \sigma_x^2 H_M(z^{-1}) H_2^*(z) & \cdots & \sigma_x^2 H_M(z^{-1}) H_M^*(z) \end{bmatrix}$$

The polynomial correlation matrix in (4.8) can be decomposed into Smith-McMillan Form (SMF) [69] using elementary matrix operations. SMF is quite elegant and extremely useful in blind channel estimation provided that proper decomposition is achievable in the following form.

$$\mathbf{R}(z^{-1}) = \sigma_x^2 \begin{bmatrix} \frac{H_1(z^{-1})}{H_1(z^{-1})} & 0 & \cdots & 0 \\ \frac{H_2(z^{-1})}{H_1(z^{-1})} & 1 & 0 & 0 \\ \vdots & 0 & \ddots & 0 \\ \frac{H_L(z^{-1})}{H_1(z^{-1})} & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & & & \\ & 0 & & \\ & & 0 & \\ & & & 0 \end{bmatrix} \begin{bmatrix} H_1^*(z) & \frac{H_2^*(z)}{H_1^*(z)} & \cdots & \frac{H_L^*(z)}{H_1^*(z)} \\ & 1 & & \\ \vdots & & \ddots & \\ 0 & 0 & & 1 \end{bmatrix} \quad (4.10)$$

For the left most matrix in the right side of (4.10), every row except the first row is multiplied by $H_1(z^{-1})$, the result is given by

$$\hat{H}_{SIMO}(z^{-1}) = \begin{bmatrix} H_1(z^{-1}) & 0 & \cdots & 0 \\ H_2(z^{-1}) & H_1(z^{-1}) & & \\ \vdots & & \ddots & 0 \\ H_L(z^{-1}) & & 0 & H_1(z^{-1}) \end{bmatrix} \quad (4.11)$$

Every column except the first column in the right most matrix in the right side of (4.10) is multiplied by $H_1^*(z)$ and obtain

$$\hat{H}_{SIMO}^*(z^{-1}) = \begin{bmatrix} H_1^*(z) & H_2^*(z) & \cdots & H_L^*(z) \\ 0 & H_1^*(z) & & \\ \vdots & & \ddots & 0 \\ 0 & & 0 & H_1^*(z) \end{bmatrix} \quad (4.12)$$

The desired channel impulse responses are readily available from either (4.11) or (4.12). (The first column in (4.11) provides the desired channel impulse responses. The first row in (4.12) is the complex conjugate of the desired channel impulse responses.) Since the SMF directly estimates the unknown channel parameters only by the use of elementary matrix operations, it is elegant and efficient.

A simple numerical example is shown here. Three subchannels are used in this SIMO model. All subchannels have order of 1, that is every channel has only one zero. The number of data samples used is 20,000. The first channel has the zero at 0.8, the zero of second channel is at 1.6, and the third channel has the zero at 1.4. Table 4.1 illustrates the estimated zeros by using the SMF, at a very high SNR.

TABLE 4.1 RESULTS OF ESTIMATED ZERO BY USING SMF, 10 RUNS

	$b_1(1) = 0.8$	$b_2(1) = 1.6$	$b_3(1) = 1.4$
$\hat{b}_m(1)$	0.8010	1.5985	1.3992
$1/\hat{b}_m^*(1)$	1.2485	0.6235	0.7128

In the case that the polynomial correlation matrix estimation has errors incurred due to the presence of additive noise or due to the unavailability of a large number of data samples, SMF still can be used to decompose the matrix. However, it is necessary to determine the greatest common divisor (GCD) among the polynomials. Finding GCD

of polynomials can be traced back to several decades ago, and in [66], Y. Hua proposed a GCD method to blindly estimate the SIMO channel parameters using a subspace technique. GCD based methods also can be used to obtain the pole-zero model from given multivariable systems in [70, 71]. Methods of GCD estimation is outside the scope of this chapter, but it is noted that GCD based methods require large eigenvalue decompositions, and thus their computational complexity is comparably high. In the following, we propose low computational complexity least squares techniques for SIMO channel estimation via the use of polynomial correlation matrix. The proposed methods comprise of two steps: an initial estimation and a refined estimation via recursion.

4.4 Estimation of a Single Subchannel via SOS and Kurtosis

At first, in the initial estimation, one subchannel is blindly estimated. As the performance of the subsequent SIMO channel estimation is based on the accuracy of the first subchannel estimation, accurate estimation of the first subchannel is necessary. Signal to noise ratio (SNR) for SIMO channel model has the same definition as that in [18] given by,

$$SNR = 10 \log_{10} \left(E \left\{ \|\bar{y}\|^2 \right\} / E \left\{ \|\bar{w}\|^2 \right\} \right) \quad (4.13)$$

where $\bar{y} = [y_1 \ y_2 \ \cdots \ y_M]$ and $\bar{w} = [w_1 \ w_2 \ \cdots \ w_M]$. The observed signal $\{y_m(n)\}$ power is given by $\sigma_{y_m}^2 = \sigma_x^2 \sum |h_m(k)|^2 + \sigma_w^2$. Since the additive noise power at each subchannel is same and the input signals to every subchannel are same, the higher the power of the received subchannel signal, the higher would be the SNR of that subchannel. Based on this, the channel with strongest received signal power can be selected for the initial subchannel estimation.

Supposed that the m^{th} subchannel is selected as the first subchannel for blind estimation. In general, this channel is a mixed phase channel, i.e., the magnitude of the channel zeros $\{b_m(k)\}$ can be smaller or larger than unity. As known, a zero inside the unit circle ($|b_m(k)| < 1$) and its reciprocal outside unit circle ($|b_m(k)| > 1$) yields the same autocorrelation sequence[10]. Therefore, for any zero estimated via an SOS based method, there would be an alternative maximum-phase zero [23]. Using SOS based methods, we can efficiently locate the minimum-phase zeros. As shown in Fig. 4.2, the m^{th} equalizer output signal $\{\hat{s}_m(n)\}$ can be expressed as,

$$\hat{s}_m(n) = s(n) \otimes h_m(n) \otimes c_m(n) + w_m(n) \otimes c_m(n) = s(n) \otimes g_m(n) + c_m(n) \otimes w_m(n) \quad (4.14)$$

The proposed technique SK in chapter 3, can be used in the strongest subchannel estimation in the SIMO channel model.

4.5 Estimation of All Subchannels using Least Squares

Using the estimated first subchannel coefficients, the remaining subchannels can be estimated via least squares techniques. We outline two approaches which uses the PCM and the equalized output, respectively.

4.5.1 Least Squares using PCM (LSPCM)

Let the estimated first subchannel coefficients be $\hat{h}_m$. It can be easily shown that the cross-correlation function between two subchannels is given by,

$$r_{mj}(l) = E\{y_m(k)y_j^*(k+l)\} = \sigma_s^2 \sum_l h_m(k)h_j^*(k+l) + \sigma_w^2 \delta(m-j) \quad l=0, \pm 1, \dots, \pm L \quad (4.15)$$

which can be rewritten in the matrix form as,

$$\begin{pmatrix} r_{mj}(-L) \\ \vdots \\ r_{mj}(0) \\ \vdots \\ r_{mj}(L) \end{pmatrix} = \begin{pmatrix} h_m(L) & 0 & \cdots & 0 \\ h_m(L-1) & h_m(L) & & \vdots \\ & & \ddots & 0 \\ h_m(0) & h_m(1) & \cdots & h_m(L) \\ 0 & h_m(0) & h_m(1) & h_m(L-1) \\ & & \ddots & 0 \\ 0 & 0 & h_m(0) & \end{pmatrix} \begin{pmatrix} h_j^*(0) \\ h_j^*(1) \\ \vdots \\ h_j^*(L-1) \\ h_j^*(L) \end{pmatrix} + \sigma_w^2 \delta(m-j) \mathbf{I} \quad (4.16)$$

where $\mathbf{I}$ is the identity matrix. For a compact representation, (4.16) can be expressed in a succinct form,

$$\tilde{\mathbf{r}}_{mj} = \tilde{\mathbf{H}}_m \tilde{\mathbf{h}}_j^* + \sigma_w^2 \delta(m-j) \mathbf{I} \quad (4.17)$$

Given $\tilde{\mathbf{r}}_{mj}$ and $\tilde{\mathbf{H}}_m$, the complex conjugate of the j^{th} subchannel impulse response can be easily obtained using a least squares approach as,

$$\tilde{\mathbf{h}}_j^* = (\tilde{\mathbf{H}}_m^T \tilde{\mathbf{H}}_m)^{-1} \tilde{\mathbf{H}}_m^T \tilde{\mathbf{r}}_{mj} \quad (4.18)$$

Therefore, using the cross-correlation function between the two subchannels obtained from the PCM, together with first subchannel coefficients $\hat{h}_m$, all other subchannels can be estimated efficiently by using (4.16)-(4.18).

4.5.2 Least Squares using Equalizer Output (LSEO)

In the channel estimation described in section 4.4, the transmitted signal is recovered at the m^{th} subchannel via an equalizer. The equalizer output signal can be used here to estimate the remaining subchannels coefficients. (for the sake of comparison we do not use the FA property at this instance.) Since the strongest subchannel is used in the estimation, the recovered signal at the equalizer output, $\{\hat{s}_m(n)\}$, is a good approximation to the input signal $\{x(n)\}$. Using $\{\hat{s}_m(n)\}$ in (4.1) we get,

$$y_j(n) = \sum_k \hat{h}_j(k) \hat{s}_m(n-k) + \hat{w}(n) \quad j=1, \dots, M, \quad j \neq m, \quad n=1, \dots, N \quad (4.19)$$

with $\hat{w}(n)$ denoting the estimation error. Knowing $\{y_j(n)\}$ and $\{\hat{s}_m(n)\}$, all the remaining j th sub-channels where $\hat{h}_j = [\hat{h}_j(0), \hat{h}_j(1), \dots, \hat{h}_j(L)]^T$, can be estimated via a least squares technique given by,

$$\hat{h}_j = (\tilde{\mathbf{s}}^T \tilde{\mathbf{s}})^{-1} \tilde{\mathbf{s}}^T Y \quad (4.20)$$

where $Y = [y_j(n_1), y_j(n_1+1), \dots, y_j(n_2)]^T$, $\tilde{\mathbf{s}} = [\tilde{s}_{n_1}, \tilde{s}_{n_1+1}, \dots, \tilde{s}_{n_2}]^T$, and $\tilde{s}_n = [\hat{s}_m(n+L), \hat{s}_m(n+L-1), \dots, \hat{s}_m(n)]$. The inverse matrix in (4.20) is of dimension $L \times L$, thus the computational load of the method is very low. Performance comparison of the methods LSPCM and LSEO will be presented in section 4.7.

4.6 Refined Estimation

The SIMO channel model shown in Fig. 4.1 has diversity, e.g. in a multiple antenna system it is the spatial diversity. It is well known that any estimation can be improved using the diversity, and thus by exploiting the SIMO channel diversity here we propose refinement to the estimation in previous section 4.5. Two possibilities are described with and without the use of FA property.

4.6.1 Refined Estimation using Channel Diversity (RECD)

Using the estimated channel parameters from the method of LSPCM, or the method of LSEO equalizers can be realized for all the subchannels. All equalizer outputs are then combined using a diversity combiner with different weights for each branch. The combined equalizers output is then used recursively in the refinement of channel estimates. Fig.4.2 depicts the structure of the refined estimation method. Note, for the sake of comparison with other existing SIMO channel estimation methods, such as the use of SOCS, the FA property is not used at the combined equalizer output.

Figure 4.2 Structure for refined channel estimation without using the FA property

In Fig.4.2, for the diversity combining, the weighting for each subchannel is obtained using the channel power, i.e.,

$$wt(m) = \hat{h}_m^* \hat{h}_m / \sum_{m=1}^M \hat{h}_m^* \hat{h}_m \quad (4.21)$$

Using the least squares estimation theory, it can be easily shown that such a combination is optimal. (The combination also has similarity to maximum ratio combination.) In Fig. 4.2, the combined equalizer output, $\{v(n)\}$ is given by,

$$v(n) = \sum_{m=1}^M \hat{s}_m(n) wt(m) \quad (4.22)$$

Using the output $\{v(n)\}$, again via a least squares technique, the refined SIMO channel coefficients matrix can be obtained as,

$$\hat{\mathbf{H}} = \mathbf{Y} \mathbf{V}^T (\mathbf{V} \mathbf{V}^T)^{-1} \quad (4.23)$$

where $\hat{\mathbf{H}} = [\hat{h}_1^T \hat{h}_2^T \cdots \hat{h}_M^T]$ and $\mathbf{Y} = [\mathbf{y}_1^T \mathbf{y}_2^T \cdots \mathbf{y}_M^T]$, and $\mathbf{V}$ has the form given by,

$$\mathbf{V} = \begin{pmatrix} v(n_1 + L) & v(n_1 + L - 1) & \cdots & v(n_1) \\ \vdots & \vdots & \ddots & \vdots \\ v(n_2) & v(n_2 - 1) & \cdots & v(n_2 - L) \end{pmatrix} \quad (4.24)$$

It has been observed in the simulations that the estimation performance is relatively independent of the selection of the two numbers n_1 and n_2 , if $n_2 - n_1$ is sufficiently

larger e.g. 10 times than the channel order. On the contrary, the performance of the use of SOCS via the subspace technique is related to the number of samples used. Thus, using a smaller number of samples one can achieve estimation results comparable or superior than the subspace estimation.

4.6.2 Refined Estimation using FA (REFA)

It is noted here that FA property is useful for improving SISO channel estimation in chapter 3. The application of the FA property in multichannel has been investigated in some works, such as in [60, 72]. However, the use of the FA property in SIMO channel estimation is ignored in most existing blind SIMO channel estimation algorithms, for example in [17, 30]. Using an FA slicer after the combiner, as shown in Fig. 4.3, here we propose the method of REFA. Although this method has similarity to the ISLP technique used with antenna arrays reported in [60], we demonstrate later that only a single recursion is needed in the proposed method to achieve near optimal channel estimation. It is also known that estimation technique which uses FA property can reach performance achieved by the use of training sequences [67].

Fig.4.3 shows the structure used in the REFA estimation, which differs from the structure in Fig. 4.2 only by the presence of the output decision-device. After projecting the equalized signal to the closest values in the FA set, it is used via a least squares estimation to achieve the best performance.

Figure 4.3 Structure for refined channel estimation using the FA property

Defining the equalized signal of Fig. 4.3 as $\{\bar{v}(n)\}$, following expressions can be

obtained in similar form to (4.24). $\hat{\mathbf{H}} = \mathbf{Y}\bar{\mathbf{V}}^T (\bar{\mathbf{V}}\bar{\mathbf{V}}^T)^{-1}$, where $\bar{\mathbf{V}}$ is given by,

$$\bar{\mathbf{V}} = \begin{pmatrix} \bar{v}(n_1 + L) & \bar{v}(n_1 + L - 1) & \cdots & \bar{v}(n_1) \\ \vdots & \vdots & \ddots & \vdots \\ \bar{v}(n_2) & \bar{v}(n_2 - 1) & \cdots & \bar{v}(n_2 - L) \end{pmatrix}$$

4.7 Simulations and Performance Comparison

In this section, simulation results of the proposed methods are presented and compared with other SIMO channel estimation techniques. The performance of SIMO channel estimation is evaluated using the normalized mean square error (NMSE), which is defined as,

$$NMSE = \frac{1}{\kappa} \sum_{l=1}^{\kappa} \frac{\|\mathbf{h} - \hat{\mathbf{h}}\|^2}{\|\mathbf{h}\|^2} \quad (4.25)$$

where κ is the number of Monte Carlo iterations used in the simulation, and $\hat{\mathbf{h}} = [\hat{h}_1, \hat{h}_2, \dots, \hat{h}_M]$ is a vector containing the estimated channel coefficients. It is noted that the proposed methods of LSPCM, LSEO and RECD are only based on statistical information, such as the SOS and kurtosis. Thus, it is fair to compare these three methods with existing statistical based methods. Only the method of REFA explicitly

uses the finite alphabet property of the transmitted signal and its performance is discussed separately later.

4.7.1 Comparison with the GCD based Method

The first example SIMO channel is as same as that used in [66] to illustrate the performance of the GCD based method of blind SIMO channel estimation. As noted earlier, the GCD is based on the determination of the common divisor among the correlation polynomials. The channel has two subchannels with coefficient vector as $h_1 = [1.1650 \ 0.0751 - 0.6965]$; and $h_2 = [0.6268 \ 0.3562 \ 1.6961]$.

TABLE 4.2 CHANNEL POWER AND ZEROS FOR THE FIRST EXAMPLE

	h_1	h_2
Channel Power	1.8480	3.3963
Channel Zeros	-0.8061 0.7416	-0.2842 + 1.6205i -0.2842 - 1.6205i

The transmitted signal is an i.i.d. QAM signal which is same as that used in [66]. White complex Gaussian noise of equal power is added at all subchannel outputs. The number of received signal in each subchannel is 200 and total Monte Carlo runs is selected as 100. The NMSE results of channel estimation for five different methods are shown in Fig. 4.4.

Figure 4.4 Proposed methods LSPCM, LSEO and RECD are compared with GCD and subspace based methods in [66].

From Fig.4.4, we can see that the proposed method LSPCM and LSEO have comparable performance to that of the GCD method. The method of RECD is better as it exploits the diversity among the SIMO channels.

4.7.2 Comparison with the Subspace Method

Second example: The number of subchannels $M=3$; the memory length of the multipath channel $L=3$; Channel coefficients are given by:

$$h_1 = [1.45 \ -2.32 \ 1.3485 \ -0.261]; \quad h_2 = [1 \ -1.75 \ 0.73 \ -0.0840];$$

$$h_3 = [0.5 \ -1.75 \ 1.87 \ -0.56];$$

The input signal is the QPSK signal.

TABLE 4.3 CHANNEL POWER AND ZEROS FOR THE SECOND EXAMPLE

	h_1	h_2	h_3
Channel Power	9.3715	4.6025	7.1230
Channel Zeros	$0.6 + 0.3i$	1.2	1.6
	$0.6 - 0.3i$	0.35	1.4
	0.4	0.2	0.5

The input sequence and the noise characteristics are as same as those of Example 1. The number of samples used in the simulation is 1024. In this example, the proposed methods are compared with the subspace technique proposed in [18]. The results are shown in Fig. 4.5(a) and (b). It is seen that the LSPCM and LSEO have comparable performance to the subspace technique. The RECD shows the best performance in Fig. 4.5(a), due to the use of channel diversity. In Fig. 4.5(b), the performance of the REFA is seen to have a dramatic improvement over the RECD method, primarily due to the use of the FA property. Furthermore, the method of REFA, using a single iteration, approaches the performance that can be obtained via training. For training estimation, via a least squares technique, the NMSE can be easily shown that

$$NMSE_{TE} = \frac{\|\mathbf{h} - \hat{\mathbf{h}}\|^2}{\|\mathbf{h}\|^2} = P_{\bar{w}} / (P_{\bar{y}} NM) \quad (4.26)$$

The Fig.4.5 also shows the results obtained using FA property in a single channel without the use of diversity combining. It is seen that using a single channel can not achieve the performance of REFA, and the difference is due to the use of diversity.

(a) Performance comparison of the proposed methods with the subspace method. 100 runs are conducted.

(b) Performance of REFA compared with training estimation, 100 runs

(c) Performance comparison of the proposed methods with the subspace method. 100 runs are conducted.

(d) Performance of REFA compared with training estimation, 100 runs

Figure 4.5 Comparison with subspace and training estimation

In order to study severe fading, the second channel power in Table 4.3 is reduced to 0.4 in the next simulation. The other channel power are kept the same. Fig 4.5(c) and (d) show the performance, which shows that the proposed methods work under severe fading.

4.7.3 SIMO Channel Estimation Performance in the Presence of Common Zeros

Third example: a common zero $z = 0.3$ is inserted to the SIMO channel model given in Table 4.3. QPSK is the inputted signal. The channel coefficients are given by,

TABLE 4.4 CHANNEL POWER AND ZEROS FOR THE THIRD EXAMPLE

	h_1	h_2	h_3
Channel Power	14.3216	6.87	10.8809
Channel Zeros	$0.6 + 0.3i$	1.2	1.6
	$0.6 - 0.3i$	0.35	1.4
	0.4	0.2	0.5
	0.3	0.3	0.3

1024 samples are used in the simulation with 100 Monte Carlo runs. The performances are shown in Fig. 4.6.

Figure 4.6 Estimation Performance of the proposed methods in a SIMO channel with common zeros.

It is seen from Fig. 4.6, that the proposed methods are effective in estimation of SIMO channel parameters even in the presence of common zeros among the subchannels. As one subchannel is estimated initially, the ratio of elements in the polynomial matrix, for example $H_1(z^{-1}) * R_{21}(z^{-1}) / R_{11}(z^{-1})$, would provide the channel coefficients even when subchannels have common zeros. It is also noted that the diversity plays an important role in SIMO channel estimation at low SNR. The combination of all equalizer outputs has improved the initial subchannel estimation.

4.7.4 Noise Power at the Equalizer Output

Note that simple zero forcing equalizers are used in the algorithms proposed here. The noise power at the output of the equalizer determines the performance of the equalizer, that means the symbol error rate (SER) is dependent on the equalizer output

noise power. Therefore, calculation of the noise power at equalizer output can be used for equalizer evaluation. (This is simpler than the exact evaluation of SER, which is extremely computationally intensive when SNR is higher than 20dB). The noise power at the equalizer output is given by,

$$\text{var}(v(n) - x(n)) \approx \hat{\sigma}_w^2 \quad (4.27)$$

If the equalized signal is away from the transmitted signal constellation, the equalizer noise power is high and the SER is correspondingly higher. In Fig. 4.7, the noise power at the equalizer output is evaluated in order to compare the proposed method in equalization. It is seen that the noise power resulting from an ideal equalizer (using true channel coefficients) and that resulting from an equalizer based on REFA estimation are identical. It also demonstrates that the use of FA property in channel estimation results in better equalization performances.

Figure 4.7 Comparison of zero-forcing equalizers in the SIMO channel estimation. 100 simulation runs.

4.8 Summary

In this chapter, we propose techniques for blind SIMO channel estimation, by extending the second order and kurtosis based techniques used in SISO channel estimation. The use of kurtosis is especially useful with communication channels as

the transmitted symbols possess non-Gaussian statistics. The proposed algorithms are simple as least squares techniques are used thus having dimensionality of matrix operations limiting at most to the channel order. The presence of common zeros among subchannels does not pose any difficulty for blind estimation. The presence of closely positioned zeros is realistic in communication channels, especially when the number of channels is higher. Channel zeros play important role in estimation, as many algorithms based on channel zeros are proposed and distribution function of wireless communication channel zeros can be found in [45]. Via simulations it is shown that the proposed algorithms achieve performances comparable or better than other existing SIMO channel estimation methods. It is also demonstrated that the performance reaches that of training performances, when the finite alphabet property of the transmitted signal is incorporated to the algorithm. Furthermore, the algorithm works with an inbuilt equalizer, thus a separate equalizer design is unnecessary. It is also shown that the proposed equalization results in error probability rates that would be achieved via equalization using ideal channel parameters. The symbol error rate can be further reduced, if better equalizers are used instead of zero-forcing equalizer [73]. Various equalizer designs and implementations are discussed in chapter 5.

Chapter 5

Zero-Based Equalizers for Single Input Single Output Channels and Single Input Multiple Output Channels

In this chapter, equalizer designs for single input single output (SISO) channels, and single input multiple output (SIMO) channels are discussed. Three kinds of equalizers: zero forcing (ZF) equalizer, minimum mean square error (MMSE) equalizer, decision feedback equalizer (DFE), are implemented for SISO and SIMO channels. The novelty of the discussed approach is that all the equalizers are designed using the channel zero information. By considering recursive filter architecture, it is shown that the proposed equalizers can be designed for efficient hardware implementation. An efficient recursive architecture for implementation is presented using the Laguerre filters. Simulations are provided to compare the differences

between the designed equalizers. The symbol error rate (SER) and the noise variance at the equalizer output are used to evaluate the equalizer performances. An equalizer application is also shown.

5.1 Introduction

It is well known that the demand for reliable and broadband data access wireless communications is rapidly growing [74]. It is anticipated that the emerging third generation wireless access systems and the use of other sophisticated modulation techniques would make such a demand achievable [75]. However, in most of these systems, the intersymbol interference (ISI) caused by limited bandwidth and the channel multipath effects are the two most major factors hindering high-speed communication. To meet the demand of high-speed and reliable communication, the equalizer employed at the receiver side of the channel plays an important role in combating the effect of ISI. Equalization of communication channels has been a problem attracting intensive research activity over the past few decades. The equalization is used not only in wireless communications, but also in some other diverse areas, such as seismology [76], image processing [77] and underwater acoustic communications [11].

At first, SISO channel equalization is addressed. The proposed SISO equalizers are based on the estimated channel zeros via techniques in chapter 3. As ZF equalizer is used in chapter 3 to obtain location of channel zeros, the details of its implementation are provided. And other equalizers, MMSE and DFE, can be thought as an extension of the ZF equalizer design. SISO Blind equalizer can be applied in wireless GSM systems [78], UWA communication systems [34, 79].

Equalizers for SIMO channels are also investigated. SIMO equalization based on the estimated channel parameters can be found in references [16, 18, 30]. The proposed equalizers here are realized based on estimation results of chapter 4. And they can be regarded as a succession of the proposed SISO equalizers. An important application of SIMO equalization is found in wireless sensor networks in [28]. The SIMO equalization also can be applied in optical systems [29], and in UWA communication systems [35, 36].

All the proposed designs in the chapter are based on the zeros of the known (estimated via training or blindly) channel transfer function. This is the novelty of the equalizer design presented in this chapter. Thus, the approach is different to the conventional equalizer design methods. It is shown that the zero based approach is simple and yet robust, and the designed equalizers can be implemented as FIR filters. We note that the zero-based equalizer design is attractive due to the existence of a number of efficient and robust zero estimation algorithms reported in the literature across numerous application areas, such as DOA estimation [41], spectrum analysis [42], and speech communications [43]. The distribution function of channel zeros for wireless communications is noted in [45].

Zero-based zero forcing (ZF) equalizer, minimum mean square error (MMSE) equalizer and decision feedback equalizer (DFE) are investigated and can be used with both SISO and SIMO channels. The MLSE (maximum likelihood sequence estimator) an equalizer with optimal performance is not addressed in this chapter, as MLSE employing Viterbi decoders usually are too complicate to employ for high data rate systems. It is shown in this chapter that the zero based design techniques possess satisfactory performances as demonstrated via simulations. As the design is based on channel zeros, the equalizer can be implemented for equalizing minimum phase

channel zeros in separation from equalizing the maximum phase channel zeros. As seen later, such a separation would aid in efficient implementation of the equalizer. Channel zero information also simplifies the DFE implementation due to separate use of minimum phase and maximum phase zeros in the DFE feed-back and feed-forward structure. Furthermore, it will be shown how the knowledge of zero locations enables one to design recursive filters with a reduced amount of computational load. It is also noted that the channel zero information plays an important role in channel estimation in that channel identifiability and estimation bounds can be directly related to the zero locations (as shown in Appendix B). As such, equalizing via channel zero locations can be justified as a natural approach to equalizer design.

Usually, the channel estimation is imperfect and the severity of the estimation error depends on the noise present in the channel. If $\hat{H}$ represents the estimated channel coefficients, ZF equalizer is simply implemented as the inverse of $\hat{H}$. As an alternative, a minimum mean square error (MMSE) structure given by $\hat{H}^H (\hat{H}\hat{H}^H + \sigma^2 I)^{-1}$ can be selected for the equalizer realization, where σ^2 is the additive noise variance, $(\cdot)^H$ is the Hermitian transpose and I is the identity matrix [17]. Although this pseudo inverse structure can be realized in different ways, the inaccurate estimation of the (unknown) noise variance would seriously deteriorate the equalization performance [18, 30]. In this chapter, based on the initial channel estimation followed by a subsequent refined estimation, an MMSE equalizer design is proposed. It is noted that the proposed design has the attractive property that it does not require the estimation of noise variance. The MMSE design, although complicated than the ZF design, avoids the noise enhancement effect of the ZF equalizer, and is especially useful under low SNR scenarios. Another approach, simpler than the MMSE design, which avoids the noise enhancement property, is the use of a DFE. In

this chapter a novel approach to the DFE design, based on the estimated channel zeros, is proposed. The DFE design approach used here is different from the traditional MMSE-DFE design which minimizes the mean square error between the input to the threshold device and the transmitted symbol, as proposed by Monsen [25].

The outline of this chapter is as follows. In section 5.2 SISO channel model and equalizers are introduced. In section 5.3, SIMO channel model and equalizers are discussed. The conceptual details of ZF, MMSE and DFE equalizers are presented in this section for the SIMO channel equalization. An efficient hardware structure for equalizer implementation is discussed in section 5.4. The simulation results demonstrating equalizer performances are illustrated in section 5.5, followed with a discussion on an application in section 5.6.

5.2 SISO Channel Model and Equalizers

Although the SISO channel has been given in chapter 3, for the purpose of convenience, it is noted again as,

$$\begin{aligned} y(n) &= y_s(n) + w(n) \\ y_s(n) &= \sum_{k=0}^L x(n-k)h(k) \end{aligned} \quad (5.1)$$

and the Z-transform of the channel transfer function is given by,

$$H(z^{-1}) = 1 + h_1 z^{-1} + \dots + h_L z^{-L} = \prod_{k=1}^L (1 - b(k)z^{-1}) \quad (5.2)$$

where $\{y(n)\}$, $\{x(n)\}$, $\{w(n)\}$, σ_w^2 and L are under same assumptions as in chapter 3.

$\{b(k)\}$ are the zeros of the channel. It is assumed here that no zeros exist on the unit circle. The channel zeros can be estimated using any existing algorithms, such as those techniques in chapter 3 of this thesis, and references therein. The design of various equalizers based on the channel zeros are discussed in the following sections.

5.2.1 Zero-Forcing equalizer

For a zero-forcing equalizer $C(z^{-1})$, $H(z^{-1})C(z^{-1})=1$, the structure is as given in Fig. 5.1.

Figure 5.1 Structure of Zero-Forcing equalizer

The equalizer can be expressed as a product of recursive filters in a cascaded form given by,

$$C(z^{-1}) = \frac{1}{H(z^{-1})} = \prod_k \frac{1}{(1 - b(k)z^{-1})} \quad (5.3)$$

The equalizer can be expressed as a product of recursive filters in parallel form given by,

$$C(z^{-1}) = \frac{1}{H(z^{-1})} = \sum_{k=1}^L H_k^B(z^{-1}) = \sum_{k=1}^L \frac{r(k)}{1 - b(k)z^{-1}} \quad (5.4)$$

where $\{b(k)\}$ are the poles (zeros of the channel) of the inverse filter and $r(k)$ are the residues associated with the poles. $r(k)$ can be calculated by the MATLAB[®] function *residuez()*. Note that, the minimum phase part in equation (5.3) and (5.4) with amplitude of pole less than unity ($|b(k)| < 1$) can be easily implemented using a simple recursive filter, or alternatively, in approximate form as an M length FIR filter given by,

$$\frac{1}{1 - b(k)z^{-1}} = \sum_{i=0}^M (b(k)z^{-1})^i \quad (5.5)$$

The value of M could be selected such that the terms neglected in the approximation are insignificant, e.g.,

$$M = \lceil \lg(\xi) / \lg(b(k)) \rceil + 1 \quad (5.6)$$

where $\lceil \cdot \rceil$ denotes the integer part of a real number. ξ is an accuracy control factor, which normally selected as $\xi = 0.01$. The maximum phase parts with $(|b(k)| > 1)$ need to be considered differently. It can be realized in FIR form with a delay D .

$$z^{-D} H_k^B(z^{-1}) = \frac{r(k)z^{-D}}{1 - b(k)z^{-1}} \cong -r(k) \sum_{i=1}^D (b(k))^i z^{-(D-i)} \quad (5.7)$$

The delay D can be selected in a similar manner as the selection of M in (5.6). When the zero $b(k)$ is close to the unit circle, the length of the FIR filter, M , becomes excessively large. In this case it is more efficient to implement the equalizer using a recursive filter architecture as described in section 5.4.

Both cascaded form and parallel form can be used for ZF equalizer implementation, but when the channel is long, the length of cascade filter will be very large. Since it requires more registers in FPGA realization, the parallel form in (5.4) for ZF equalizer design is preferred.

5.2.2 Minimum Mean Square Error (MMSE) Equalizer

It is also possible to design a minimum mean square error (MMSE) equalizer based on the channel zeros. The transfer function of the equalizer implemented under the MMSE criterion is given by [11],

$$\frac{H^*(z)}{H(z^{-1})^* H^*(z) + N_0} \quad (5.8)$$

with $*$ denoting the complex conjugation operating on the channel coefficients. For the MMSE design, it is required to estimate the unknown additive Gaussian noise power spectral density N_0 , to evaluate the denominator of (5.8). In the following we present a novel approach for the MMSE equalizer design without resorting to noise

power estimation. The method is based on a refinement to the channel estimation using the equalizer output, in a single recursion, as described below.

Suppose that the channel parameters are estimated by any existing SOS or HOS statistics based methods, e.g. as in [26, 54]. Let the estimated channel is given by $H_1(z^{-1}) = (1 - \hat{b}(1)z^{-1})(1 - \hat{b}(2)z^{-1}) \cdots (1 - \hat{b}(L)z^{-1})$, and we then note that, $H_1(z^{-1})$ incorporates the effect of the additive noise in the channel [80]. Based on $H_1(z^{-1})$ the channel can be (approximately) equalized to obtain an output $\{\hat{s}(n)\}$. As shown in [54], via a single recursion of the equalizer output $\{\hat{s}(n)\}$, the initial estimation $H_1(z^{-1})$ can be improved to obtain $H_2(z^{-1})$.

All equalized output data $\{\hat{s}(n)\}$ is projected to the nearest appropriate FA symbol set, to obtain an estimate of the transmitted signal $\{v(n)\}$. Cross correlation of $\{v(n)\}$ and the observed noisy signal $\{y(n)\}$ would then provide the channel coefficients of the unknown system $H_2(z^{-1})$. That is, using the least squares method in chapter 3 to obtain a refinement to the initial estimates as given by $H_2(z^{-1})$. Using $H_1(z^{-1})$ and $H_2(z^{-1})$, in the MMSE equalizer design, equation (5.8) can be rewritten as,

$$\frac{H_2^*(z)}{H_1(z^{-1}) * H_1^*(z)} \quad (5.9)$$

(5.9) can be designed in the same way as that of (5.4). As elaborated later, the MMSE equalizer does improve the symbol error rate (SER) performance of the equalization compared to a ZF equalizer, especially under low SNR conditions.

5.2.3 Decision Feedback Equalizer (DFE)

Over the last three decades, the use of Decision feedback equalizers (DFEs) has become popular in digital communication applications in mitigating intersymbol

interference (ISI) [11, 25, 80]. The DFE is a nonlinear symbol-by symbol detector, which contains two linear filters: a feedforward filter, and a feedback filter. The feedback from previously decoded symbols is used in ISI compensation. DFE equalizer provides a good compromise between performance and complexity, obtaining a much better performance than a linear equalizer, at a much lower complexity than the optimum detector—the maximum likelihood sequence estimator (MLSE). In the present discussion, we consider a DFE where both feedforward filter (FFF) and feedback filter (FBF) are FIR filters. The explicit structure of the DFE is illustrated in the Fig. 5.2, (more precisely this belongs to a DFE-ZF architecture). The equalizer output can be expressed as,

$$s(n) = \sum_{j=-L_f}^0 f_j y_{n-j} + \sum_{j=1}^{L_b} b_j v_{n-j} \quad (5.10)$$

where $\{f_j\}$ are the filter-tap gains of the FFF, L_f is the length of the FFF; $\{b_j\}$ are the filter-tap gains of the FBF, L_b is the length of FBF, and $\{v(n)\}$ is an estimate of the n^{th} transmitted information symbols. Note that the assumption of sufficiently accurate detection of the transmitted symbol is necessary which is often satisfied in the DFE at high SNR.

Figure 5.2 Decision feedback equalizer

In a conventional DFE design, one minimizes the cost function $J = E\{(s(n) - v(n))^2\}$, and the DFE tap gains can be obtained by directly solving the Wiener-Hopf equation [80]. However, in here, to reduce the computational

complexity, we propose a different approach which uses the already available channel zero information. Noting that the channel is comprised of minimum phase zeros and maximum phase zeros, we separately consider the DFE design for the minimum phase part and the maximum phase part. Let the two DFE filters, FFF and FBF, are given respectively by the transfer functions $F_k(z^{-1})$ and $B_k(z^{-1})$. Ignoring the effect of the decision device, it can be easily shown that the system transfer function in Fig. 5.2 is given by,

$$F_k(z^{-1})/(1 - B_k(z^{-1})) \quad (5.11)$$

However, FBF in Fig. 5.2 need to be a minimum phase filter (i.e. a causal filter) so that output detection can be used in ISI compensation. Thus for a minimum phase zero, e.g. the k th channel zeros, the DFE can be implemented easily by selecting FFF and FBF in the following manner.

$$F_k(z^{-1}) = 1 \quad \text{and} \quad B_k(z^{-1}) = 1 - b(k)z^{-1}. \quad (5.12)$$

For a maximum phase zero, we first observe that,

$$\frac{1}{(1 - b(k)z^{-1})} = \frac{(1 - b(k)^{-1}z^{-1})}{(1 - b(k)z^{-1})(1 - b(k)^{-1}z^{-1})} = \frac{(1 - b(k)^{-1}z^{-1})}{(1 - b(k)z^{-1})} \frac{1}{(1 - b(k)^{-1}z^{-1})} \quad (5.13)$$

The first term on the right side of (5.13) is an all pass filter. The all pass filter can be realized in the FIR form with a delay in a similar form as described in equation (5.7). The second term on the right side of (5.13) represents a minimum phase filter, and thus the DFE implementation can be realized as,

$$F_k(z^{-1}) = \frac{(1 - b(k)^{-1}z^{-1})}{(1 - b(k)z^{-1})} \quad \text{and} \quad B_k(z^{-1}) = (1 - b(k)^{-1}z^{-1}) \quad (5.14)$$

Consider all channel zeros, the over-all FFF transfer function of the DFE can be expressed as,

$$F(z^{-1}) = \prod F_k(z^{-1}) \quad (5.15)$$

while the over-all transfer function of the FBF is given by,

$$B(z^{-1}) = 1 - \prod B_k(z^{-1}) \quad (5.16)$$

The tap gains of the FFF $\{f_j\}$ and FBF $\{b_j\}$ are now resulting from $F(z^{-1})$ and $B(z^{-1})$, respectively.

In the appendix C, a bidirectional zero based decision feedback equalizer is proposed. The idea is an extension of the zero based DFE in this section. Since the time-reversal operation is extremely useful for block transmission systems, such as in UWA communication [81], in medical imaging [82], the BiZDFE has important practical applications.

5.3 SIMO Channel Model and Equalizers

The single input multiple output (SIMO) models are widely used to exploit the spatial diversity of communication channels. Here we would investigate receiver equalizers for SIMO channels that are designed based on the channel zero information. A discrete-time SIMO FIR model as same as (4.1) is considered as,

$$y_m(n) = \sum_k h_m(k)s(n-k) + w_m(n) \text{ for } m=1, 2, \dots, M \quad n=1, 2, \dots, N \quad (5.17)$$

Let $\mathbf{h}_m = [h_m(0), h_m(1), \dots, h_m(L)]$ denote the finite impulse response (FIR) characteristics of the m^{th} subchannel, $H_m(z^{-1})$ represent the Z-transform of the subchannel impulse response $\mathbf{h}_m$ and $b_m(k)$ be the k^{th} zero of the m^{th} subchannel. The $((L+1)*M)$ channel coefficients matrix is $\mathbf{H} = [h_1^T \ h_2^T \ \dots \ h_M^T]$. Assumptions of SIMO model are same as those in chapter 4. The block diagram of SIMO multipath channel and equalizer is illustrated in Fig 5.3.

5.3.1 Zero-Forcing Equalizer

Based on the above discussed SIMO model, the structure for SIMO ZF and MMSE equalizers is shown at the right most part in Fig.5.3. In the following, how the structure in Fig.5.3 can be implemented using the channel zero information is discussed.

Figure 5.3 The ZF and MMSE equalizer structure for SIMO channels

The conjugates of the filter responses required at each channel output in Fig.5.3 are obtained from the estimated channel coefficients (e.g. any existing methods, such as those in [17-19, 54] can be used). In the conventional ZF equalization of SIMO channel as in [16, 18] the zero-forcing equalizer $C(z^{-1})$ is obtained as the pseudo inverse given by $\hat{H}^H (\hat{H}\hat{H}^H)^{-1}$. From Fig.5.3, we note that the equalizer, $C(z^{-1})$ can be written as,

$$C(z^{-1}) = 1 / \sum_{m=1}^M |H_m(z^{-1})|^2 \quad (5.18)$$

where

$$\sum_{m=1}^M |H_m(z^{-1})|^2 = \sum_{m=1}^M H_m(z^{-1}) \otimes H_m^*(z) = \alpha \prod_{i=1}^{2L} (1 - c_i z^{-1}) \quad (5.19)$$

α being a normalization factor and $H_m(z^{-1})$ is the channel transfer function of the m^{th} subchannel in the SIMO model. On the left hand side of (5.19), $\{c_i\}$ are the zeros of equalizer transfer function. By evaluating the zeros $\{c_i\}$, the ZF equalizer for SIMO channel can be realized in a cascade FIR form as done for SISO channel in section II.A. When zeros $\{c_i\}$ are closer to the unit circle, a recursive equalizer architecture proposed in section 5.4 would be useful for better efficiency in hardware implementation.

5.3.2 Minimum Mean Square Error Equalizer

As noted before, the MMSE equalizer design, although more complicated than the ZF design, avoids the noise enhancement effect of ZF equalizers. The transfer function of the SIMO equalizer based on the MMSE criterion is [16, 18, 30],

$$C(z^{-1}) = \hat{\mathbf{H}}^H (\hat{\mathbf{H}}\hat{\mathbf{H}}^H + \sigma^2 I)^{-1} \quad (5.20)$$

As the additive noise variance σ^2 is unknown, [16, 18, 30] estimate σ^2 from the singular values of the estimated signal covariance matrix. Observing the autocorrelation matrix of the received signal, it can be seen that [83],

$$R_Y = R_s + R_w = \sigma_s^2 \mathbf{H}\mathbf{H}^H + \sigma^2 I \quad (5.21)$$

The covariance matrix R_Y is composed of a signal term R_s (independent of noise), and a noise term R_w . The effect of noise, in the form of σ^2 appears along the main diagonal of the autocorrelation matrix of the received signal. Thus, without using the SVD to find the value of σ^2 , the correlation polynomials of the diagonal element of autocorrelation matrices can be used in the inverse operation appearing in the design of equalizer $C(z^{-1})$ in (5.21). That is, equation (5.20) can be expressed as,

$$C(z^{-1}) = \hat{\mathbf{H}}^H (R_Y)^{-1} \quad (5.22)$$

As in the SISO design, a refined channel estimation is used to replace $\hat{H}$ of equation (5.22). Thus, it is straight-forward to implement the MMSE equalizer for SIMO model based on the information of channel zeros.

5.3.3 Decision Feedback Equalizer

DFE equalizers for SIMO channels can be realized using the architecture shown in Fig.5.4. The input signal of the DFE is the observed signal at each sub-channel in (5.17). The DFE architecture in Fig. 5.4 is different from the traditional MMSE-DFE for SIMO channels which uses optimization techniques to search for the parameters of feedback and feedforward filters, as described in [29]. In this section, a decision feedback equalizer for SIMO channels, where both FFF and FBF are designed based on the channel zeros, is described.

Figure 5.4 Decision feedback equalizers structure for SIMO channel

Again, in the DFE design, the minimum phase channel zeros and the maximum phase channel zeros are considered separately. Recall that $b_m(k)$ is the k^{th} zero of the m^{th} subchannel, and let $F_{mk}(z^{-1})$ be the contribution from this zero to FFF and, similarly, $B_{mk}(z^{-1})$ is the contribution to FBF. The FFF and FBF contributions for a minimum phase zero can be easily obtained as,

$$F_{mk}(z^{-1}) = 1 \text{ and } B_{mk}(z^{-1}) = 1 - b_m(k)z^{-1} \quad (5.23)$$

For a maximum phase zero, similarly to the SISO DFE design, the FFF and FBF contributions are obtained as,

$$F_{mk}(z^{-1}) = \frac{(1 - b_m^{-1}(k)z^{-1})}{(1 - b_m(k)z^{-1})} \text{ and } B_{mk}(z^{-1}) = (1 - b_m^{-1}(k)z^{-1}) \quad (5.24)$$

Using (5.23) and (5.24), the over-all FFF transfer function of the DFE for m^{th} sub-channel is expressed as,

$$F_m(z^{-1}) = \prod F_{mk}(z^{-1}) \quad (5.25)$$

where as the over-all transfer function of the FBF filter is given by,

$$B_m(z^{-1}) = 1 - \prod B_{mk}(z^{-1}) \quad (5.26)$$

Note that η_m in Fig. 5.4 is the feedback ISI compensating signal from the previously detected symbols for the m^{th} subchannel as given by,

$$\eta_m(n) = \sum_{j=-L_f}^0 f_m(j)y_m(n-j) + \sum_{j=1}^{L_b} b_m(j)v(n-j) \quad (5.27)$$

where $\{f_m(n)\}$ and $\{b_m(n)\}$ are the impulse response of the feed-forward and feedback filters for m^{th} subchannel. All η_m are averaged before used in the decision device in Fig.5.4.

5.4 Efficient Laguerre Structure for Equalizer Design

All proposed ZF, MMSE and DFE equalizers for SISO and SIMO channels in above sections are based on FIR filters designed using the channel-zero information. As can be seen from equations (5.5) and (5.7), when the channel zeros are closer to the unit circle, the FIR filter length would be excessively large. For such cases, we consider efficient equalizer implementation via recursive filter architecture. Such architecture is useful in finite word-length circuit implementations, such as in the designs using FPGA (Field Programmable Gate Arrays) or ASIC techniques with

limited hardware resources. Noting that recursive filters are unstable in general, a robust and hardware efficient Laguerre filter [46, 84, 85] architecture is discussed here as a possible means for equalizer implementation. (It has been shown that due to the balanced requirement on the memory and combinatorial circuits, the Laguerre filter can be easily optimized when implemented using FPGA [32].) Noting that equation (5.4) can be re-written via the following truncated Laguerre series,

$$H_k^B(z^{-1}) = \frac{r_k}{1-b(k)z^{-1}} \cong \sum_{i=0}^M r_{i,k} \phi_i(z^{-1}) \quad (5.28)$$

where $r_{i,k}$ is the Laguerre series coefficients and $\phi_i(z^{-1})$ is the frequency domain Laguerre function, given by,

$$\phi_i(z^{-1}) = \frac{\sqrt{1-a^2}}{1-az^{-1}} \left(\frac{z^{-1}-a}{1-az^{-1}} \right)^i; \quad \left(\begin{array}{l} -1 \leq a < 1 \\ i = 0, 1, \dots, M-1 \end{array} \right) \quad (5.29)$$

and a is the Laguerre filter pole. When $a=0$ the Laguerre filter defined in equation (5.28) becomes an M -length FIR filter. Consider minimum phase zeros, where $|b(k)| \leq 1$, and using the following transformation:

$$t = \frac{z^{-1}-a}{1-az^{-1}} \Rightarrow z^{-1} = \frac{t+a}{1+at} \quad (5.30)$$

(5.28) can be rewritten as,

$$H_k^B(z^{-1}) = \frac{r_k}{1-b(k)z^{-1}} \cong r_k \left(\frac{\sqrt{1-a^2}}{1-az^{-1}} \right) \sum_{i=0}^M r_{i,k} \left(\frac{z^{-1}-a}{1-az^{-1}} \right)^i$$

where

$$r_{i,k} = \frac{\sqrt{1-a^2}}{1-ab(k)} \left(\frac{b(k)-a}{1-ab(k)} \right)^i \quad (5.31)$$

since $|b(k)| \leq 1$, the coefficients $r_{i,k}$ are monotonically decreasing with increasing values of i . Therefore, the Laguerre series expansion could be approximated by truncation to M terms, and the value of M could be obtained in a similar form to equation (5.6), i.e.,

$$\left| \frac{b(k) - a}{1 - ab(k)} \right|^M = 10^{-2} \Rightarrow M = -2 / \log_{10} \left(\left| \frac{b(k) - a}{1 - a|b(k)|} \right| \right) \quad (5.32)$$

For maximum phase zeros, when $|b(k)| > 1$, equation (5.28) can be expressed in the following form,

$$H_k^B(z^{-1}) = -\frac{r_k z b(k)^{-1}}{1 - b(k)^{-1} z} \cong r_k \left(\frac{1 - az^{-1}}{z^{-1} - a} \right)^M \left(\frac{\sqrt{1 - a^2}}{1 - az^{-1}} \right)^{M-1} \sum_{i=0}^{M-1} r_{i,k} \left(\frac{z^{-1} - a}{1 - az^{-1}} \right)^i$$

$$\text{where } r_{i,k} = -\frac{\sqrt{1 - a^2}}{b(k) - a} \left(\frac{1 - ab(k)}{b(k) - a} \right)^{M-1-i} \quad (5.33)$$

and M can be selected as

$$\left| \frac{1 - ab(k)}{b(k) - a} \right|^M = 10^{-2} \Rightarrow M = -2 / \log_{10} \left(\left| \frac{1 - a|b(k)|}{|b(k)| - a} \right| \right) \quad (5.34)$$

In general, when the zero locations are unknown, the selection of a closer to the unit circle would result in a lesser number of multipliers in the filter implementation. However, choosing a closer to unit circle would result in unacceptable magnitudes for limit cycles and thus a compromised value need to be used in the design [46]. Since the zeros of the branch filters in (5.28) is known, it is possible to design the Laguerre filter optimally as described in the following section.

An Example: consider the following ZF equalizer implemented using the Laguerre filter architecture. The Laguerre filter pole is selected as $a = 0.75$ (or $3/4$) so that the

pole could be represented using 2 bits. In this way, the Silicon area needed can be saved in hardware implementations. The bit growth of the data path after each multiplication can be also controlled. Furthermore, any multiplication by a can be implemented by a few adders and subtractors. Following Table 5.1 shows the number of multipliers required for implementing the branch filter stages for different values of the pole $b(k)$ of the estimated inverse channel transfer function [46, 86].

TABLE 5.1 NUMBER OF MULTIPLIERS REQUIRED FOR FILTER IMPLEMENTATION USING FIR AND LAGUERRE ARCHITECTURE [46, 86].

$ b(k) $	Implemented as FIR Filter	Implemented as Laguerre Filter
0.05	1	14
0.15	2	11
0.40	5	6
0.60	9	3
0.90	43	5
0.95	89	12
1.05	95	14
1.10	49	7
1.30	18	2
2.00	7	6
5.00	3	11

It can be seen that the Laguerre architecture requires a significantly less number of multipliers in the implementation when the pole $|b(k)| \rightarrow 1$. When the pole is away from the unit circle, an FIR implementation is the suitable choice. (Ideally the pole a should be chosen equal to the channel zero, but this may be impractical under implementation constraints.) Using equations (5.32) and (5.34) it is easy to show that in the following range of the filter pole a the Laguerre implementation is advantageous over an FIR implementation

$$\frac{1 - \sqrt{1 - a^2}}{a} \leq |b(k)| \leq \frac{1 + \sqrt{1 - a^2}}{a} \quad (5.35)$$

For $a = 0.75$, equation (5.35) results in $0.45 \leq |b(k)| \leq 2.21$. Based on equation (5.35) it is proposed to implement the Laguerre ZF equalizer in the following manner.

- (a) An FIR filter to account for the poles outside the range in equation (5.35). The effect of all the poles in this range could be lumped together to realize a single FIR filter. Poles greater than 1 (maximum phase) will result in non-causal implementations.
- (b) The effect of all the poles in the range in equation (5.35) is realized by a single Laguerre filter. Again maximum phase poles would result in a non-causal implementation which requires a maximum phase all-pass filter. The Laguerre filter will be operated in parallel to the FIR filter.

5.5 Equalizer Performance Analysis

In this section, simulation results are presented to illustrate the performance of the proposed equalizers. In the simulations, the channel input signals are selected as i.i.d. QPSK sequences having zero mean. The additive channel noise is modeled as a complex white Gaussian processes with zero-mean and independent to the channel input. The simulations are described separately for SISO channels and SIMO channels.

5.5.1 SISO Channel Simulation

For the simulations, the SNR is defined as in chapter 3 for SISO channel.

Simulation channel I: The system transfer function of the 3rd order NMP model used in the simulations is given by $H(z^{-1}) = 1 - 0.9z^{-1} + 0.385z^{-2} + 0.771z^{-3}$ which has channel zeros at 0.6 and $0.75 \pm j0.85$. This channel is widely cited in the literature and has been used in [8] and references therein. Note that one channel zero

is situated inside the unit circle while the other two zeros lie outside the unit circle. The symbol error rates resulting at the equalizers are shown in Fig. 5.5, for the SNR range of 2 to 16. The number of samples in each run is $N=2048$. The total number of error symbols calculated for every simulation point is 100. From results in Fig. 5.5, we conclude that the equalizers work satisfactorily and that the DFE provides the best performance.

Figure 5.5. The symbol error rates resulting from ZF, MMSE, DFE equalizers for SISO channel equalization. SNR varies from 2 to 16 dB.

5.5.2 SIMO Channel Simulation

In this section, simulation results are presented to illustrate the performance of the proposed SIMO equalizers. The SNR for SIMO model is defined same as that in chapter 4. The input signal is selected from QPSK constellations.

A SIMO system with three, third order subchannels has been used in the simulation. The first channel having a coefficient vector $\{1-3.12.68 -0.42\}$ has two maximum phase zeros and one minimum phase zero. The second channel coefficient vector is $\{1-2.62.16-0.576\}$, and has two minimum phase zeros and a one maximum phase zero. The third channel is an all minimum phase channel with

coefficient vector $\{1 - 1.60.93 - 0.18\}$ comprising of two complex zeros and one real zero.

In the simulations, the equalizer output noise variance, $\text{var}(\hat{s} - v)$ is used as a criterion to evaluate the equalizer performances. The output noise variances are shown in Fig 5.6. Note that the initial SIMO channel estimation is done using the CR method [19]. The channel estimation is subsequently improved by using a least squares recursive (LS) technique as discussed in chapter 4. Fig. 5.6 shows the noise variance at outputs of ZF and DFE equalizers based on the estimation results by CR and LS. For comparison, performances of equalizers implemented using the ideal channel parameters are also shown. Not surprisingly, Fig. 5.6 shows that the equalizer performances do not depend heavily on the channel estimation. The DFE using the ideal channel parameters performs the best. For both ZF and DFE equalizers, the use of LS provides estimation results as good as the use of ideal parameters. In the simulations, as the SNR in the SIMO system is not small enough, the advantage of MMSE is not obviously seen. (The MMSE noise variances are similar to ZF results at higher SNR, and are not shown in Fig 5.6.) MMSE has better performance than ZF in single channel systems [73] when SNR is low. This conclusion is also true for SIMO channel equalization results shown in Fig. 5.7.

Figure 5.6 Noise variance at SIMO equalizers output, SIMO channel parameters are obtained by CR[19], LS and ideal channel.

Fig. 5.7 shows the symbol error rates (SER) of different equalizers designed via the results obtained by the LS method. It is seen that the MMSE has better performance than ZF when the SNR is low and the DFE has the best performance among all the equalizers. Note that the symbol error rates (SER) are estimated using the output noise variance. Since SER estimation using noise variances has a much lower computational load than for direct SER computation, Fig. 5.7 provides a more efficient means of equalizer evaluation. The number of samples in each run is $N=2048$. The total number of error symbols calculated for every simulation point is 100.

Figure 5.7 The SER performance of ZF, MMSE, DFE for SIMO Channel Equalization

5.5.3 Comparison of Laguerre Equalizers with FIR Equalizers

It was shown in section 5.4 that when channel zeros are closing on to the unit circle, a Laguerre filter has the advantage over FIR filters in hardware implementations. As an example, consider the communication system described by (2.3). Suppose that the transmitted symbols $\{s(n)\}$ are from a QPSK modulation scheme, and the multi-path channel transfer function, constitutes of two poles, maximum phase and minimum phase, at $(1.30-j0.10)$ and $(0.70+j0.10)$. The signal-to-noise ratio is given by $30dB$. A residue equalizer was implemented at the receiver using the Laguerre filter architecture with $a=0.75$. Fig. 5.8 shows the un-equalized and equalized signals at the receiver. The equalizer has successfully separated the received signal into the correct constellations. Fig. 5.8 also shows results from an FIR zero-forcing filter which produces almost similar performance to the Laguerre filter. However, the FIR implementation needed 32 multipliers whereas the Laguerre implementation required only 7 multipliers. This exemplifies the effectiveness of the Laguerre equalizer over the FIR equalizer in hardware implementations.

Figure 5.8 Performance of Laguerre Structure ZF-Equalizer

In Fig. 5.8, the top figure is the received signal corresponding to a QPSK transmission. The below-left is FIR ZF equalized signal constellations. The below-right is equalized signal from a Laguerre ZF Implementation. SNR is 30 dB.

5.6 Application in Underwater Acoustic Communications

Demand for high speed underwater acoustic (UWA) communication is increasing, as the underwater applications shift from exclusive military use to commercial applications [37]. UWA communication can be applied in areas, such as environment monitoring, underwater exploration, scientific data collection, ocean bottom detection. If techniques for UWA communication were mature enough, people would find more energy resources under water, the conflict on territorial sea between countries could be less, and the recently happened Tsunami tragedy in Indian Ocean could have been avoided. This section addresses blind techniques for UWA communication channel equalization. It also serves as an application example of the proposed techniques in this thesis. Firstly, the characteristics of UWA channel are presented. Then the signal processing for UWA communications is addressed. The spatial diversity equalization for UWA communication is the main concern of this section. Finally, a numerical example is provided to demonstrate the performance of the proposed techniques.

5.6.1 UWA Communications Channel Characteristics

As cables are heavy and expensive for deployment, wireless communications is in demand for underwater communications. Due to high attenuation property of the seawater, radio communication is not feasible. And optical communication only can be used in short range. Acoustic communication is the most suitable choice. A large amount of research activities in UWA communication are emerging.

Attenuation for underwater channel can be expressed as, $A(d, f) = d^k a(f)^d$ [36], where k is the frequency and d is the distance. $a(f)$ is an increasing function in f . We can see that the attenuation is increasing with frequency and distance. It shows that the distance of UWA communication can not be too far and the speed can not be too fast. What's more, it makes the available bandwidth for communication very limited, thus, bandwidth-efficient modulation, such as a coherent modulation technique QPSK, is needed for high-rate communications.

Noise in underwater environment is more severe than the noise in radio communication systems. One category of the noise is site-specific, it includes man-made, biological (shrimp) and effect of rain and so on. The other is ambient, for example, turbulence, shipping, thermal etc. Power spectral density (PSD) of the most ambient noise is continuous and they have Gaussian statistics. It is approximated that noise PSD decays at $b=18$ dB/dec. The SNR for UWA channel can be approximated as $SNR(d, f) \approx 10 * k * \log d - d * 10 * \log a(f) - b * 10 \log f$, so the noise effect makes UWA communication more difficult than radio communication.

The other major problem that obstructs the UWA communication is multipath propagation. For shallow water, reflections from surface, bottom and other objects contribute to the multipath effect. It is noted that reflections at surface have little loss. Reflection loss at bottom is stronger, but it depends on the type of bottom, as sand and rock have different effect. Also angle of incidence and frequency are major factors

affect the intensity of loss. Multipath effect will be attenuated with repeated reflection loss and increased path length. In order to investigate the UWA communication, suitable models for prediction is required. Impulse response of a UWA multipath channel can be obtained via an equivalent baseband model as,

$$h(\tau) = \sum g_p \exp(-j\omega_c \tau_p) \delta(t - \tau_p) \quad (5.36)$$

where $g_p = \Gamma_p / A_p^{1/2}$ and $A_p = A(l_p, f)$ is p^{th} path attenuation; Γ_p is p^{th} path reflection coefficient. l_p is the p^{th} path length. $\tau_p = l_p / c$ is the p^{th} path delay

The UWA channel is time-variant due to a large amount of factors, such as water movement, turbulence, surface motion and so on. Time variation will cause signal fading. The above properties of UWA channel cause severe intersymbol interference (ISI) [11] and obstruct high speed transfer. In order to combat ISI and reach the target of high speed acoustic communication, channel equalization techniques are adopted at the receiver.

5.6.2 Channel Equalization for UWA Communications

Different from various types of equalizers used in radio communication systems, channel-estimation based equalizer is a major choice for UWA communication systems, such as in [34, 35, 87, 88]. Channel parameters are estimated via a preamble packet, it is assumed that the channel is invariant during this period. This technique is suitable for high speed acoustics transfer system, where the most important factor is computational complexity, that is, the channel can be assumed to be constant over the transmission period of the preamble packet [88]. The proposed blind channel estimation techniques can be used in such UWA communication systems if the channel is slow varying, however, the proposed equalizers still are useful even fast varying channels. Equalization is the focus of this section.

It is shown in [89] that multipath decision feedback equalizer (DFE) jointly with a phase locked loop (PLL) has obvious advantage over passive phase conjugation (PPC) techniques in reducing ISI when there are a small number of receivers. Note also that DFE is a nonlinear equalizer, a good compromise between performance and complexity, obtaining a much better performance than a linear equalizer at a much lower complexity than for the optimum detector, the maximum likelihood sequence estimator (MLSE) [25]. DFE is a popular equalization technique adopted in UWA communications [37, 89].

In this section, the proposed zero based DFE in chapter 5 is applied to underwater acoustic communication channel equalization. Compared with the conventional channel coefficients based MMSE-DFE, which requires inversion of a matrix that may have high computational complexity [89], the proposed technique here is more efficient and faster in optimum selection of the equalizer. The performance of the proposed equalizer for communication channels is demonstrated in a simulated shallow water environment. The performance of the initial channel estimation can be updated by exploiting the finite alphabet property at the decision feedback equalizer output.

The block diagram of the use of DFE in UWA communications is shown in Figure 5.9. The equalizer coefficients are estimated and updated using training data in the least square channel estimation algorithm.

Figure 5.9 Block of single channel equalization for UWA communications

5.6.3 Multiple Channel Equalization for UWA Communications

Spatial diversity equalizers applied to UWA communications has drawn a lot of research interest, and one can find applications in [35, 79] and references therein. The availability of multiple and uncorrelated measurements of the transmitted signal is called as diversity. Diversity can be achieved in frequency, time or space from the statistical point of view. It is noted that diversity can increase the SNR of the received signal with uncorrelated measurements. Diversity plays an important role in UWA communications.

When multiple receivers are used to improve performance via diversity combining, the recently single input multiple output (SIMO) channel model as discussed in chapter 4 can be used for describing UWA channel. The zero based SIMO multipath decision feedback equalizer (DFE) can be used to achieve spatial diversity in UWA communication channels with the assumption of accurate timing recovery.

The SIMO DFE for UWA spatial diversity equalization is shown in Fig. 5.10 as,

Fig 5.10 Multipath Channel Equalizer for UWA Communications

The novelty of the proposal is that the SIMO DFE equalizer is designed using the estimated channel zeros, which is faster than the use of traditional MMSE-DFE. The estimation results are compared with blind SIMO channel estimation bounds and the training channel estimation performances.

5.6.4 Simulation Examples

An example used here for simulation refers to the Shallow Water Channel (SWC) [88]. We assume that there are two receivers and the sampling rate at the receiver is baud rate. The multipath channels are assumed to be time-invariant during the data transfer period. Channel impulse responses of the multipath channels are given by,

$$h_i(t) = \sum_{j=-4}^4 \alpha_{ij} p(t - \tau_{ij}) \quad (5.37)$$

where the amplitude of each ray α_{ij} is in matrix from,

$$[\alpha_{ij}] = \begin{pmatrix} 1 & 0.3421 & -0.1235 & -0.2936 \\ 1 & 0.2631 & 0.1512 & 0.3916 \end{pmatrix} \quad (5.38)$$

and τ_{ij} the time delay to the first ray is selected as,

$$[\tau_{ij}] = \begin{pmatrix} 0 & 0.7800 & 2.1300 & 2.9300 \\ 0 & 0.3500 & 1.9600 & 3.3550 \end{pmatrix} T \quad (5.39)$$

where T is the symbol period. And $p(t)$ is a raised cosine impulse shape with roll off factor 20%. Length of channels is $\{-4 \ 4\}$ symbols. The modulated signal is QPSK. The channels consist of additive white Gaussian noise, with SNR (signal to noise ratio) of 20dB. Performance of equalization using ideal channel parameters is shown in Fig. 5.11.

The most important observation is that the computational time of the zero based DFE is less than that of the MMSE-DFE. The first channel in (5.37) is used as an example. Computational time of zero-based DFE is compared with computational time of MMSE-DFE. Two MMSE-DFEs with different lengths of feedforward filter and feedback filter are used for comparison. They all have same long feedback filters, whose order is equal to the order of channel. The results are shown in Table 5.2.

Table 5.2 Computation time of zero-based DFE

Zero-based DFE lf= 23, lb=8	MMSE-DFE lf=23, lb=8	MMSE-DFE lf=15, lb=8
0.0050 ms	0.0180 ms	0.0068 ms

where l_f is the length of FFF, l_b is the length of FBF. From Table 5.2, we can see that computation of zero-based DFE is faster than that of MMSE-DFE even MMSE-DFE has shorter feedforward filter. If they has same long feedforward filter, zero-based DFE is almost three times faster than MMSE-DFE. This is very useful for UWA communications, as high speed equalization techniques are necessary for time varying UWA channels.

QPSK is used as the transmitted signal with SNR equal to 20dB. The received signal at first receiver is shown at the right of Fig. 5.11. And the equalized signal

using zero based SIMO DFE is shown the left of Fig. 5.11. It is shown that the proposed SIMO-DFE is suitable for UWA communication equalization.

Fig.5.11 Equalization performance of the proposed SIMO equalizer for SWC communication.

Symbol error rate (SER) performance of the proposed zero based SIMO DFE equalizer is compared with conventional MMSE-DFE [89], the lengths of FFF and FBF of DFEs are same. In Fig. 5.12, it is shown that the proposed ZF-DFE has better performance when SNR is larger than 10 dB, although conventional MMSE-DFE has marginally better performance when SNR is low. This conclusion also is supported by the discussion in [89].

Fig 5.12 Comparison of ZF-DFE and MMSE-DFE in UWA communication channel.

5.7 Summary

In this chapter, three kinds of equalizer are implemented for SISO channels and SIMO channels. The novelty of the proposed implementations is that all equalizers are designed based on (blindly) estimated channel zeros. Not surprisingly, it has been demonstrated that the zero forcing equalizer enhances the noise in the channel, but the linear MMSE equalizer, although complicated in implementation, provides better noise immunity than the ZF equalizer. At higher SNR, the nonlinear equalizer—DFE equalizer—achieves the best performance with ease in hardware implementation. (The described DFE in the chapter has the DFE-ZF architecture. Simulation of DFE-MMSE architecture has shown no additional advantages.) It is also shown that using the FA property of the transmitted signal, the initial channel estimation can be improved. In this case the designed equalizers reach ideal performances for channel equalization. The use of the channel zeros in the equalizer design enables one to implement filters in hardware in an efficient manner. An application of the proposed equalizer in a UWA communication environment is discussed.

Chapter 6

Conclusions and Future Work

The objective of blind channel estimation and equalization to recover the transmitted signal, which is corrupted by noise in a frequency-selective multipath channel, is achieved in this thesis. Conclusions based on the proposed zeros based channel parameter estimation and equalization algorithms for SISO and SIMO channels and their applications are presented in section 6.1. Then future research works are discussed in section 6.2.

6.1 Conclusions

At first, algorithms based on channel zero information are reviewed. In some areas, information of channel zeros plays an important role in system identification. According to the work in [45], where the distribution function of wireless communication channel zeros is presented, it is shown that channel-zero based estimation techniques are also important for wireless communications. Using the existing SOS based methods, the channel zero estimation for minimum phase systems

is addressed. In order to evaluate the proposed techniques, bounds for channel zero estimation and channel coefficient estimation are presented in appendix A. Restrictions, such as zeros are assumed to be complex conjugate pair, are not used in the analysis. This discussion serves as the benchmark of this thesis.

As most practical channels are not minimum phase and channel parameters are unknown for the receiver, blind channel parameter estimation for single user communication system is addressed based on the channel zero information. It is shown that non-minimum phase information, such as FA and kurtosis, can be used to solve the ambiguity of channel zeros location without resorting to complicated higher order statistics. The zeros distribution information of NMP channel and its impact on the channel parameter estimation are analyzed in appendix B.

With multiple sensors or receivers are used at the communication receiver, the channel model is regarded as a SIMO channel model. Using the techniques in SISO model and cross-relationship between all subchannels, it is shown that reliable SIMO channel parameter estimation is feasible.

In order to recover the transmitted signal subjected to noise and multipath effect, equalizer is an important tool in combating ISI. The existing equalizer designs are reviewed. As it is known that linear and nonlinear equalizers have their own advantage and disadvantage, both kinds of equalizers are implemented for SISO and SIMO channels for comparison. ZF, MMSE, DFE equalizer design methods are investigated, which are based channel zeros.

If the communication signal is transmitted in a block mode, a bidirectional zero based decision feedback equalizer (BiZDFE) can be used. An equalizer suitable for such a communication system is proposed in appendix C. BiZDFE consists of two parallel DFE structures, one equalizes the received signal in normal time sequence

and the other utilizes the time-reversed version of the received signal. The structure is efficient in minimizing error propagation and also results in a low bit error rate. In addition, for a minimum phase channel or a maximum phase channel, the BiZDFE can reduce the length of equalizer filter, which is the major concern in any FPGA implementation. Such equalizers can be applied in time-reversal acoustic communication, which is a very active research area currently [81, 82].

In recent years, the demand of high-speed data transfer has been increased in UWA communication. Applications of the proposed equalizers in UWA communication channels are also discussed.

6.2 Future work

The channel zeros based channel estimation and equalization for SISO and SIMO channels have been discussed. It is possible to extend these ideas to MIMO (Multiple Input Multiple Output) [90] channel parameter estimation and equalization. Normally MIMO channel coefficients can be estimated by semi-blind or training estimation techniques. And FIR equalizer can be used for MIMO equalization [80, 90]. So channel zeros based equalizers are also suitable for MIMO system.

In chapter 3 and appendix B, the bounds for NMP channel estimation are discussed, but it was only feasible for low SNR and high SNR cases as it is an approximation to the NMSE. Cramer-Rao Low Bound (CRLB) is a theoretical bound to compare the performance of any unbiased estimator. The difficulty of evaluating bounds for NMP channel estimation is the ambiguity information of the zeros location as noted in Appendix B. The evaluation of CRLB is a problem to be investigated in the future.

In chapter 4, the strongest channel is used in the first step estimation, as it determines the results of the second step. A more robust technique for the selection of strongest

channel is desired. A bounds for SIMO channel estimation can be found in [83]. But this bound is a deterministic bound, and not statistic based bound, and the bound could be changed with different input signals. A more appropriated bound is required.

Although the UWA channels are generally confined to low data rates as compared to a radio channel, the encountered channel distortions make UWA communications more challenging. As the span of UWA channel can last several hundred symbols duration, the practical DFE design may need to be tap-selective. Although researchers have proposed many equalizers in literature, such as [36, 39, 40, 91], the commercial version of these in underwater acoustic modems is not feasible. Designing a practical, low-cost, real-time equalizer (modem) for UWA communications is another future research direction.

As the emergence of third generation wireless communication systems, such as Wideband Code Division Multiple Access (WCDMA) [92], the high speed data transfer becomes practical. The application of proposed algorithms in real communication systems is another future work.

Appendix A

Proof of Equations

Equation (2.3) also can be expressed via a discrete variable

$$y(t) = h(0)x(t) + h(1)x(t-1) + h(2)x(t-2) + \dots + h(L)x(t-L) + w(t) \quad (\text{A.1})$$

The following relationship can be obtained,

$$x(t) = \frac{1}{h(0) + h(1)z^{-1} + h(2)z^{-2} + \dots + h(L)z^{-L}} (y(t) - w(t)) \quad (\text{A.2})$$

From (2.4), we know that

$$H(z^{-1}) = \sum_{k=0}^L h(k)z^{-k} = \prod_{k=1}^L (1 - b(k)z^{-1})$$

Gradients of $x(t)$ with respect to channel zeros can be obtained by differentiating (A.1)

as,

$$\begin{aligned} \frac{\partial x(t)}{\partial b(m)} &= - \frac{-z^{-1} \prod_{k=1, k \neq m}^L (1 - b(k)z^{-1})}{\left(h(0) + h(1)z^{-1} + h(2)z^{-2} + \dots + h(L)z^{-L}\right)^2} (y(t) - w(t)) \\ &= \frac{z^{-1} \prod_{k=1, k \neq m}^L (1 - b(k)z^{-1})}{H(z^{-1})} x(t) \end{aligned} \quad (\text{A.3})$$

Let $D_m(z^{-1}) = z^{-1} \prod_{k=1, k \neq m}^L (1 - b(k)z^{-1}) [H(z^{-1})]^{-1}$, and coefficients of Z-transform function

$D_m(z^{-1})$ are $\{d_{m,n}\}$ in (A.3) can be rewritten as,

$$x'_t = \frac{\partial x(t)}{\partial b(m)} = d_{m,0}x(t) + d_{m,1}x(t-1) + d_{m,2}x(t-2) + \dots \quad (\text{A.4})$$

As given in [44], for larger N, the fisher information matrix (FIM) for data is,

$$I_y(b) = \frac{1}{\sigma_x^4} E \left[\sum_{t=1}^N x_t (\nabla_b x_t) \sum_{s=1}^N x_s (\nabla_b x_s) \right] \quad (\text{A.5})$$

According (A.3) and (A.4), (A.5) can be rewritten as,

$$I_y(b)_{m,n} = \frac{1}{4\sigma_x^2} \left[\sum_{u=0}^{\infty} d_{m,u} d_{n,u} \sum_{t=1}^N E(x_t^2 x_{t-u}^2) \right] = N \sum_{u=0}^{\infty} d_{m,u} d_{n,u} \quad (\text{A.6})$$

Gradients of $x(t)$ with respect to channel coefficients can be obtained by differentiating (A.1) as,

$$\frac{\partial x(t)}{\partial h(m)} = -\frac{z^{-m}}{(h(0) + h(1)z^{-1} + h(2)z^{-2} + \dots h(L)z^{-L})^2} (y(t) - w(t)) = -\frac{z^{-m}}{H(z^{-1})} x(t) \quad (\text{A.7})$$

And the fisher information matrix for channel coefficients is given by,

$$I_y(h)_{m,n} = \frac{1}{4\sigma_x^2} \left[\sum_{u=0}^{\infty} \tilde{d}_{m,u} \tilde{d}_{n,u} \sum_{t=1}^N E(x_t^2 x_{t-u}^2) \right] = N \sum_{u=0}^{\infty} \tilde{d}_{m,u} \tilde{d}_{n,u} \quad (\text{A.8})$$

where $\tilde{d}_{m,u}$ are coefficients of the Z-transfer function given by

$$\tilde{D}_m(z^{-1}) = -z^{-m} [H(z^{-1})]^{-1}.$$

Appendix B

Bounds for NMP Channel Estimation

Let the true NMP channel $H(z^{-1})$ and the estimated channel $\hat{H}(z^{-1})$ can be expressed as a product of a minimum phase and all pass transfer functions, i.e.

$$H(z) = H_{MP}(z^{-1})H_{AP}(z^{-1}) \quad ; \quad \hat{H}(z) = \hat{H}_{MP}(z^{-1})\hat{H}_{AP}(z^{-1}) \quad (\text{B.1})$$

Assuming un-biased estimation we get,

$$\sum_{k=0}^L (h(k) - \hat{h}(k))^2 = \sum_{k=0}^L \hat{h}(k)^2 - \sum_{k=0}^L h(k)^2 \quad (\text{B.2})$$

where $h(k)$ and $\hat{h}(k)$ are the coefficients of polynomials $H(z^{-1})$ and $\hat{H}(z^{-1})$ respectively, (B.2) can be expressed as,

$$\begin{aligned} &= \hat{H}(z^{-1})\hat{H}^*(z) \Big|_{z=1} - H(z^{-1})H^*(z) \Big|_{z=1} \\ &= \hat{H}_{MP}(z^{-1})\hat{H}_{MP}^*(z) \Big|_{z=1} - H_{MP}(z^{-1})H_{MP}^*(z) \Big|_{z=1} \end{aligned} \quad (\text{B.3})$$

Equation (B.3) shows that the MSE of the NMP channel is as same as that of an equivalent MP channel. The bounds for estimation $H_{MP}(z^{-1})$ has been shown in approximate form as,

$$bound = \left(P_w / \sigma_x^2 + tr(I_h^{-1}) \right) / \sum |h(k)|^2 \quad (\text{B.4})$$

The fisher information matrix I_h is given in (A.8) in appendix A. Thus, the above bound (B.4) in conjunction with equation (B.3) can be used for performance comparison in NMP channel coefficient estimation.

Impact of Non-Gaussianity on Estimation $\hat{H}_{AP}(z^{-1})$

It is well known that blind SISO channel estimation fails when the input is Gaussian. That is $\hat{H}_{AP}(z^{-1})$ of equation (B.1) can not be properly estimated using any

HOS techniques. To evaluate the impact of non-Gaussianity on estimation, we note that equation (3.12) can be equivalently expressed as,

$$S(z) = H(z)C(z)X(z) + C(z)W(z) \quad (\text{B.5})$$

At high SNR , assuming that the MP zeros can be accurately estimated using SOS, we get $\hat{H}_{MP}(z^{-1}) = H_{MP}(z^{-1})$. However, $\hat{H}_{AP}(z^{-1})$ can not be correctly estimated as the phase information is not used in the SOS. Using (B.1), (B.3), (B.5) can be rewritten as,

$$S(z) = \frac{H_{MP}(z)H_{AP}(z)}{\hat{H}_{MP}(z)\hat{H}_{AP}(z)} X(z) = \prod_{\text{some } b(k)} |b(k)|^2 \left[\frac{1 - z^{-1}/b(k)^*}{1 - b(k)z^{-1}} \right] = \sum \alpha(k)z^{-k} \quad (\text{B.6})$$

where the all pass section is resulting from the reflection of one or more MP zeros on the unit circle.

For evaluation, the channel used in [54], a third order NMP model with system zeros -0.6 and $0.75 \pm j0.85$ is selected. The system transfer function is $H(z) = 1 - 0.9z^{-1} + 0.385z^{-2} + 0.771z^{-3}$. For this channel, 3 other channels having same MP zeros and power can be obtained as,

$$\begin{aligned} H_1(z^{-1}) &= 0.771 + 0.385z^{-1} - 0.9z^{-2} + 1.0z^{-3}, \\ H_2(z^{-1}) &= 0.6 + 0.1z^{-1} - 0.729z^{-2} + 1.285z^{-3}, \\ H_3(z^{-1}) &= 1.285 - 0.729z^{-1} + 0.1z^{-2} + 0.6z^{-3} \end{aligned} \quad (\text{B.7})$$

For the example channel $H(z^{-1})$ and the 3 other equivalent channels noted in (B.7), there would be 4 branch impulse responses, $\sum \alpha(k)z^{-k}$, resulting from equation (B.6). These are shown in Fig. B.1, where the top figure notes a delta function corresponding to the properly equalized branch. It was shown in chapter 3, that using the cost function in equation (3.17), the channel zeros can be correctly located, i.e. $\hat{H}_{AP}(z^{-1})$ can be properly estimated.

Figure B.1 Branch impulses responses resulting from channel transfer function and 4 different equalizer transfer function realizations. Top one corresponds to correct equalizer branch.

Using $\sum \alpha(k)z^{-k}$, the expected value of the cost function $E[J(\varphi)]$, of equation (3.17) for each branch can be expressed in a simplified form as,

$$E \left[\frac{K(x_n)}{E^2 \{|x_n|^2\}} \frac{K(s_n|\varphi)}{E^2 \{|s_n|\varphi|^2\}} \right] = \left(2 - \frac{K(x)}{E^2 \{|x|^2\}} \right) \left(1 - \frac{\sum \alpha^4(k)}{[\sum \alpha^2(k)]^2} \right) \quad (\text{B.8})$$

Note that the second term on the right hand side of (B.8) is always non-negative and is zero for proper equalization (as in the top line of Figure 2). The probability distributions for $J(\varphi)$ resulting from simulating the 4 branch outputs are shown in Fig. B.2. Note that in Fig. B.2 the zero mean density corresponding to the proper equalizer branch, and increasing the level of modulation (e.g. from 4 to 16 constellations) reduces the separation of the distributions. When the input is Gaussian, $K(x)/E^2 \{|x|^2\} = 2$. Then the right hand of (B.8) is always zero and thus the equalization is not possible.

An i.i.d. quadrature phase shift keyed (QPSK) random sequence with zero mean is used as the input signal $x(n)$ having power of σ_x^2 . For a given input and given

channel, it is possible to obtain the distributions in Fig. B.2 in approximate analytical form. Therefore, the MSE resulting from selection of $\hat{H}_{AP}(z^{-1})$ can also be determined.

Figure B.2 Probability density of the cost function of equation (B.8) for the four branches, resulting from a 16 – QAM input sequence.

For the given channel in section 3.4, for QPSK inputs this MSE is given by,

$$MSE = 6.29 \times \text{erfc}(5.18) \quad (\text{B.9})$$

When the MSE in (B.9) is larger than the bound in (B.4), we could say that the non-Gaussianity has an impact on the NMP channel estimation and the MSE is determined by (B.9) rather than bound in (B.4).

Appendix C

Bidirectional Zero-Based Decision Feedback Equalizers (BiZDFE)

C.1 Introduction

In this appendix, a new bidirectional decision feedback equalizer (BiDFE) is proposed. The novelty of the proposed structure is that the proposed equalizer is based on channel zeros, which is different from traditional BiDFE designs. The proposed bidirectional zero-based decision feedback equalizer (BiZDFE) efficiently exploits the time reversal operation, which results in that zeros of the equivalent channel seen from equalizer are the reciprocals of the actual channel zeros. It is shown that BiZDFE is more efficient in fading channel equalization than BiDFE and traditional MMSE-DFE.

Over the last three decades, the use of *Decision feedback equalizers* (DFEs) has been reported in digital communication applications to mitigate ISI [11, 25]. DFE equalizer provides a good compromise between performance and complexity, obtaining a much better performance than a linear equalizer at a much lower complexity than that of the optimum detector—the MLSE. Time-reversal DFE technique has drawn research interest since [93], as time reversal operation results in that the equivalent channel seen from equalizer are the reciprocals of the actual channel zeros (the equivalent channel impulse response is the time-reverse of the actual channel impulse response [93]). BiDFE has two branches [94], one DFE is used for normal time sequence equalization, the other DFE is used for time-reversal sequence equalization. As channel diversity is exploited, BiDFE has better performance over traditional DFE [80, 94]. We consider the DFE where both

feedforward filter (FFF) and feedback filter (FBF) are FIR filters based on channel zeros, as an FIR filter is more robust in filter implementation [95, 96].

C.2 Proposed BiZDFE

For a single-user system, the discrete-time base-band model is a time-invariant single-input single-output (SISO) system described as [1],

$$\begin{aligned} y(n) &= y_s(n) + w(n) \\ y_s(n) &= \sum_{k=0}^L x(n-k)h(k) \end{aligned} \quad (C.1)$$

Then the over-all FFF transfer function of the DFE can be expressed as,

$$F(z^{-1}) = \prod_{i=1, |b(i)| > 1}^L \frac{(1-b(i)^{-1}z^{-1})}{(1-b(i)z^{-1})} \quad (C.2)$$

while the transfer function of the feedback filter is,

$$B(z^{-1}) = 1 - \prod_{i=1, |b(i)| > 1}^L (1-b(i)^{-1}z^{-1}) \prod_{i=1, |b(i)| < 1}^L (1-b(i)z^{-1}) \quad (C.3)$$

[93] notes that by reversing the observed signal $\{y(n)\}$ before equalization, the equivalent channel impulse response changes to the time-reversal of the actual channel impulse response. The time-reversed channel transfer function can be expressed as,

$$\bar{H}(z^{-1}) = h(0) + h(1)z + \dots + h(L)z^L = \prod_{i=1}^L (1-b(i)z) = c \prod_{i=1}^L z(1-b(i)^{-1}z^{-1}) \quad (C.4)$$

where constant $c = (-1)^L \prod_{i=1}^L b(i)$ can be directly derived from the channel zeros. From

(C.4) and (2.4), we can see that the zeros of the time-reversal channel are the reciprocal of the original zeros of the normal mode channel in (2.4). A DFE can be used to equalize the time-reversal signals. Using (C.2) and (C.3), the coefficients of the FFF and FBF of time-reversal DFE are,

$$F_{TR}(z^{-1}) = \frac{1}{c} \prod_{i=1, |b(i)| < 1}^L \frac{(1 - b(i)z^{-1})}{(1 - b(i)^{-1}z^{-1})} \quad (C.5)$$

$$B_{TR}(z^{-1}) = 1 - \prod_{i=1, |b(i)| > 1}^L (1 - b(i)^{-1}z^{-1}) \prod_{i=1, |b(i)| < 1}^L (1 - b(i)z^{-1}) \quad (C.6)$$

As seen from (C.5), the coefficients of the FFF of time-reversal DFE is composed of the minimum phase zeros of the original channel. This is the major difference with normal model DFE. When the original channel is maximum phase channel or has more maximum phase zeros than minimum phase zeros, the FFF of the time-reversal DFE can be simpler than that of normal model DFE. From (C.3) and (C.6), we can see that the coefficients of the FBF of the normal model DFE and the time-reversal DFE are same. This property will reduce the complexity of DFE realization.

The explicit block structure of the BiZDFE is illustrated in Fig. C.1. BiZDFE has two branches, the first branch is for normal time sequence equalization. This DFE equalizer output can be expressed as,

$$y_1(n) = \sum_{j=-L_f}^0 f_j y_{n-j} + \sum_{j=1}^{L_b} b_j \tilde{v}_{n-j} \quad (C.7)$$

where $\{f_j\}$ are the tap coefficients of the FFF, L_f is the length of the FFF; $\{b_j\}$ are the tap gains of the FBF, L_b is the length of FBF. $\{\tilde{v}(n)\}$ is an estimate of the n^{th} information symbols. The assumption of accurate detection of the previous symbol is necessary and is often satisfied in the DFE.

The second branch is for time-reversed sequence equalization. The sampled signal $\{y(n)\}$ is reversed in time-domain before feedings into the following DFE. Subsequently, the DFE output is time reversed again to obtain the equalized signal $\{y_2(n)\}$. The equalized signals of two equalizers are combined together before used at the input of the decision device shown in Fig.C.1.

Figure C.1. The Block Structure of Bidirectional Zero based Decision Feedback Equalizers (BiZDFE)

C.3 Simulation results

In this part, three different channels are used in the simulation. The input signal is selected as 16-QAM signal having zero-mean. The three channels are a minimum phase channel $h_1 = [1.285 \ -0.729 \ 0.10.6]$; a mixed phase channel $h_2 = [0.771 \ 0.385 \ -0.9 \ 1]$; and a maximum phase channel $h_3 = [0.6 \ 0.1 \ -0.729 \ 1.285]$. Definition of SNR is as same as that used in chapter 3. The number of samples in each run is $N=2048$. The total number of error symbols calculated for every simulation point is 100. SER is used as the criterion to evaluate the equalizer performance. The performance of BiZDFE in these channels is compared with those of traditional BiDFE in [80]. The results are illustrated in the following.

The first example is the minimum phase channel noted above. In Fig.C.2(a), BiZDFE is compared with zero-based DFE of [73] and time-reversal zero-based DFE. That is the performance of signal $\{v(n)\}$ in compared with signals $\{y_1(n)\}$ and $\{y_2(n)\}$. Similar to ZF design, MMSE design can also be used for bidirectional equalization. In Fig.C.2(b), BiMMSEDFE is compared with traditional MMSE-DFE [11] and time-reversal MMSE-DFE.

(a)

(b)

Fig. C.2 Performance of BiZDFE in minimum phase channel

In Table C.1, we list the length of all FFFs and FBFs used in Fig.C.2

Table C.1 Length of FFFs and FBFs for minimum phase channel

	Normal Zero based DFE	Time-reversal Zero based DFE	Normal MMSE-DFE	Time-reversal MMSE-DFE
lf	1	127	15	15
lb	3	3	3	3

For a minimum phase channel, the zero-based DFE can be realized using a very short filter. And it still can achieve similar performance compared to the other equalizers. However, because of short FFF, the performance of normal zero-based

DFE is not as good as that of time-reversal zero-based DFE, which has a very long FFF.

The second example is the maximum phase channel noted earlier. The inputted signal is 16-QAM signal. SNR definition is same as noted earlier. Results are shown in Fig.C.3(a) and Fig.C.3(b). The number of samples in each run is $N=2048$. The total number of error symbols calculated for every simulation point is 100.

(a)

(b)

Fig. C.3 Performance of BiZDFE in maximum phase channel

In Table C.2, the lengths of all FFFs and FBFs used in Fig.C.3 are listed.

Table C.2 Length of FFFs and FBFs for maximum phase channel

	Normal Zero based DFE	Time-reversal Zero based DFE	Normal MMSE-DFE	Time-reversal MMSE-DFE
lf	127	1	15	15
lb	3	3	3	3

For maximum phase channel, the FFF of time-reversal zero-based DFE can be realized using a very short filter. On the other hand, the FFF of normal zero based DFE is very long. Different from the performance of time-reversal MMSE-DFE, time-reversal zero-based DFE does not improve the equalization performance, as its FFF only has one tap. But the results still are encouraging, because such a short equalizer can provide close performance achieved by other longer equalizers. This property is useful in FPGA implementations to reduce the number of registers used. Also it can improve the efficiency of hardware design.

The third example is the mixed phase channel noted above. Results are shown in Fig.C.4(a) and Fig.C.4(b). The inputted signal is 16-QAM signal. SNR definition is same as noted earlier. The number of samples in each run is $N=2048$. The total number of error symbols calculated for every simulation point is 100.

(a)

(b)

Fig. C.4 Performance of BiZDFE in mixed phase channel

In Table C.3, the lengths of all FFFs and FBFs used in Fig.C.4 are listed.

Table C.3 Length of FFFs and FBFs for mixed phase channel

	Normal Zero based DFE	Time-reversal Zero based DFE	Normal MMSE-DFE	Time-reversal MMSE-DFE
lf	15	113	15	15
lb	3	3	3	3

For mixed phase channel, the time-reversal zero-based DFE and normal zero-based DFE have close performance as shown in Fig.C.4, although their FFFs have different length shown in Table C.3. However, use of the diversity combining [93], has provided the BiZDFE the best performance among all equalizers.

The long filter lengths in Table C1-C3 can be reduced by interchanging the filtering operators in equations (C.2) and (C.5) with a time reversal. This is new structure is shown in Fig. C.5.

Figure C.5. The new block structure of the proposed BiZDFE

The filters $\tilde{F}$ and $\tilde{F}_{TR}$ can be efficiently implemented by changing z^{-1} to z in these equations. $\tilde{B}$ and $\tilde{B}_{TR}$ are same as B and B_{TR} of BiZDFE. From Fig.C.1 and Fig.C.5, the proof is given by,

$$y(z)F_{TR}(z^{-1}) = y(z^{-1})\tilde{F}_{TR}(z^{-1})|_{z=z^{-1}} \quad (C.8)$$

It is easy to see that $\tilde{F}_{TR}(z^{-1}) = F_{TR}(z)$, and $\tilde{F}(z^{-1}) = F(z)$ is true obviously.

C.4 Summary

In this appendix, a novel zero-based bidirectional decision feedback equalizer is proposed. The proposed BiZDFE makes full use of time-reversal operation, which results in an equivalent channel with zeros as the reciprocal of the actual zeros. Performance of the proposed equalizer is compared with traditional equalizers in minimum phase, mixed-phase and maximum phase communication channels. The results show that the proposed BiZDFE has good performance. An alternative structure is proposed aimed to reduce the filter length.

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