ITERATIVE DETECTION AND DECODING FOR MIMO-OFDM USING EM BASED CHANNEL ESTIMATION

A DISSERTATION

Submitted in partial fulfillment of the requirements for the award of the degree

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(With Specialization in Communication Systems)

By

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CANDIDATE'S DECLARATION

I hereby declare that the work, which is presented in this dissertation report entitled, **"ITERATIVE DETECTION AND DECODING FOR MIMO-OFDM USING EM BASED CHANNEL ESTIMATION"** towards the partial fulfillment of the requirements for the award of the degree of **Master of Technology** with specialization in **Communication Systems**, submitted in the Department of Electronics and Computer Engineering, Indian Institute of Technology Roorkee, Roorkee (India) is an authentic record of my own work carried out during the period from July 2009 to June 2010, under the guidance of **Dr.D.K.MEHRA, Professor, Department of Electronics and Computer Engineering, Indian Institute of Technology Roorkee.**

I *have not submitted the matter embodied in this dissertation for the award of any other* Degree or Diploma.

Date: 15-6-2010
Place: Roorkee

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CERTIFICATE

This is to certify that the above statement made by the candidate is correct to the best of my knowledge and belief.

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ABSTRACT

OFDM has become a popular technique for transmission of signals over wireless channels. It converts a frequency-selective channel into a parallel collection of frequency flat sub channels, which makes the receiver simpler. A MIMO system takes advantage of the spatial diversity obtained by spatially separated antennas in a dense multipath scattering environment. For high data-rate transmission, the multipath characteristic of the environment causes the MIMO channel to be frequency-selective. OFDM can transform such a frequency-selective MIMO channel into a set of parallel frequency-flat MIMO channels, and therefore decrease receiver complexity. The combination of the two powerful techniques, MIMO and OFDM, is very attractive, and has become a most promising broadband wireless access scheme. For detection of OFDM signals, channel must be known at the receiver. Channel estimation is a challenging problem in wireless systems.

The expectation-maximization (EM) algorithm provides an iterative approach to likelihood-based parameter estimation when direct maximization of the likelihood function may not be feasible. The EM algorithm consists of two major steps: an expectation step, followed by a maximization step.

In this dissertation work, we consider EM and EM-MMSE based channel estimation techniques for OFDM systems. EM-MMSE technique is computationally simpler than EM technique. Following this, hard VBLAST-EM based channel estimation for MIMO-OFDM systems will be discussed. In this approach a plain VBLAST algorithm is used for data detection. Finally, soft VBLAST-EM based channel estimation for MIMO-OFDM systems is considered. Soft VBLAST algorithm is an improved VBLAST, which takes the error propagation effect into account. IDD (Iterative Detection and Decoding) block is used to further improve the performance of MIMO-OFDM system. Simulation results are also presented.

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INTRODUCTION

The gradual evolution of wireless communication systems follows the quest for high data rates (bps). The first-generation (1G) radio systems used analog communication techniques to transmit voice over radio. The 2G systems were built with digital technology, such as Global System for Mobile Communications (GSM), Digital-AMPS (D-AMPS), code-division multiple access (CDMA), and personal digital cellular (PDC), among them GSM is the most successful and widely used 2G system. To accomplish higher data rates, two add-ons were developed for GSM, namely high-speed circuit switched data (HSCSD) and the general packet radio service (GPRS), providing data rates up to 38.4 Kbit/s and 172.2 Kbit/s, respectively. The demand for yet higher data rates forced the development of a new generation of wireless systems, known as third generation (3G) [1].

3G wireless technologies provide users with high-data-rate wireless access. The three major radio air interface standards for 3G are wideband CDMA (WCDMA), time-division synchronous CDMA (TD-SCDMA), and cdma2000. The transmitted data rate of 3G is up to 144 kb/s for high-mobility traffic, 384 kb/s for low-mobility traffic, and 2 Mb/s in good conditions. One of the leading technologies for 3G systems is the now well-known universal mobile telephone system (UMTS). To yield the 3G data rates, an alternative approach was made with the enhanced data rates for GSM evolution (EDGE). The wireless communication system with features of high data- rate transmission and open network architecture, called 4G, is desired to satisfy the increasing demand for broadband wireless access. Hence, 4G refers to a collection of technologies and standards that will find their way into a range of new widespread computing and communication systems. The key objectives of 4G are to provide reliable transmission with high peak data rates ranging from 100 Mb/s for high mobility applications to 1 Gb/s for low-mobility applications, high spectrum efficiency up to 10 b/s/Hz, and ubiquitous services that can accommodate various radio accesses.

Orthogonal frequency division multiplexing (OFDM) has become a popular technique for transmission of signals over wireless channels. OFDM has been adopted in several wireless standards such as digital audio broadcasting (DAB), digital video broadcasting (DVB-T), the IEEE 802.11a local area network (LAN) standard and the IEEE 802.16a metropolitan area network (MAN) standard. OFDM converts a frequency selective channel into a parallel collection of frequency flat sub-channels. For detection of OFDM signals, channel must be known at the receiver [2].

Channel estimation is a challenging problem in wireless systems. Where, unlike other guided media, the radio channel is highly dynamic. The transmitted signal travels to the receiver by undergoing many detrimental effects that corrupt the signal and often place limitations on the performance of the system. Transmitted signals are typically reflected and scattered, arriving at receivers along multiple paths. Also, due to the mobility of transmitters, receivers, or scattering objects, the channel response can change rapidly over time. Multi path propagation, mobility, and local scattering cause the signal to be spread in frequency, time, and angle. These spreads, which are related to the selectivity of the channel, have significant implications on the received signal [3].

Different techniques are proposed to exploit these statistics for better channel estimates. These techniques can be classified as pilot-aided or blind channel estimation. In the pilot-aided channel estimation technique, a pilot sequence known at the receiver is embedded into the signal. At the receiver side, using these pilot symbols and the received signals, the channel is estimated. On the other hand, blind channel estimation techniques do not use any training symbols. They use the received signals and stochastic information of transmitted and received signals to estimate the channel coefficients. A widely used blind estimation technique is the subspace-based channel estimation. In this method, the autocorrelation matrix of the received data is decomposed into the signal and noise subspaces by using singular value decomposition (SVD) technique.

Compared to pilot aided techniques, blind techniques save on the use of pilots and can thus increase the spectral efficiency. However, blind techniques require prior knowledge of stochastic information of the transmitted and received signals. Moreover, they always result in poorer performance compared to pilot-aided techniques.

Multiple antennas can be used at the transmitter and receiver, this arrangement is called as a multiple-input multiple-output (MIMO) system. A MIMO system takes advantage of the spatial diversity that is obtained by spatially separated antennas in a dense multi path scattering environment. MIMO systems may be implemented in different ways to obtain either a diversity gain to combat signal fading or to obtain a capacity gain. Generally, there are three categories of MIMO techniques. Such techniques include space–time block codes (STBC), spatial multiplexing(SM) and space–time trellis codes (STTC). In Layered space time architecture (LST), codes are expressly meant for improving multiplexing gain by transmitting M_T independent data steams. In LST, by nature the data streams are orthogonal to each other. There are two major types of classification of spatial multiplexing – horizontal encoding (HE), and vertical encoding (VE). A variant of vertical encoding (VE) is the vertical BLAST architecture.

Multiple transmit-and-receive antennas can be used with orthogonal frequency division multiplexing (OFDM) to improve the communication capacity and quality of mobile wireless systems. Most of MIMO techniques are developed for flat fading channels. However, multi path will cause frequency selectivity of broadband wireless channels. Therefore, MIMO-OFDM, which has originally been proposed to exploit OFDM to mitigate ISI in MIMO systems, turns out to be a very promising choice for future high-data-rate transmission over broadband wireless channels. MIMO-OFDM has become a very popular area in wireless communications. A real-time FPGA prototype for a 4-stream MIMO-OFDM transceiver capable of transmitting 216Mbit/s in 20MHz bandwidth is considered in [4]. To obtain the promised increase in data rate, accurate channel state information is required in the receiver.

The Expectation-Maximization (EM) algorithm is a technique for finding maximum likelihood estimates of system parameters in a broad range of problems where observed data are incomplete. The EM algorithm consists of two iterative steps: the expectation step and the maximization step. The expectation step is performed with respect to unknown underlying parameters, using the current estimate of the parameters, conditioned upon the incomplete observations. The maximization step then provides a new estimate of the parameters that maximizes the expectation of log likelihood function defined over complete data, conditioned on the most recent observation and the last estimate. These two steps are iterated until the estimated values converge [9].

1.1. Statement of the problem

This dissertation work is aimed at performance study of EM based channel estimation for OFDM and MIMO-OFDM systems.

The dissertation presents the following work

1. Study and implementation of EM and EM-MMSE based channel estimation for OFDM systems in Rayleigh multipath fading channel model with both stationary and time varying environment.
2. Study and implementation of hard/soft VBLAST-EM based channel estimation for BICM MIMO-OFDM systems in time varying fading environment.
3. Implementation of iterative detection and decoding (IDD) used to improve the performance of soft VBLAST-EM based channel estimation for BICM MIMO-OFDM systems.

1.2. Organization of the Report

This report is organized in five chapters:

In *chapter 1,* Introduction and the statement of problem of the dissertation work is summarized.

In *chapter 2,* base-band OFDM system model is described first. Next, techniques for channel estimation for OFDM systems are described. Briefly EM algorithm, EM and EM-MMSE based channel estimation techniques for OFDM systems are discussed.

In *chapter 3*, VBLAST detection algorithm is described first. Next, BICM MIMO-OFDM system model is described. Conventional EM and hard VBLAST-EM based channel estimation for MIMO-OFDM systems are discussed next.

In *chapter 4*, Channel estimation for BICM MIMO-OFDM systems using soft VBLAST-EM technique is presented. Iterative detection and decoding (IDD) is discussed. Simulation results are also presented.

Chapter 5 gives the conclusion of the thesis work.

Chapter 2
EM BASED CHANNEL ESTIMATION FOR OFDM SYSTEMS

In this chapter, base-band OFDM system model is described first. Next, techniques for channel estimation for OFDM systems are described. EM algorithm, EM and EM-MMSE based channel estimation techniques for OFDM systems are discussed. Next, simulation results on the performance of above channel estimation techniques in OFDM systems are presented at the end.

2.1. Base-Band OFDM System Model:

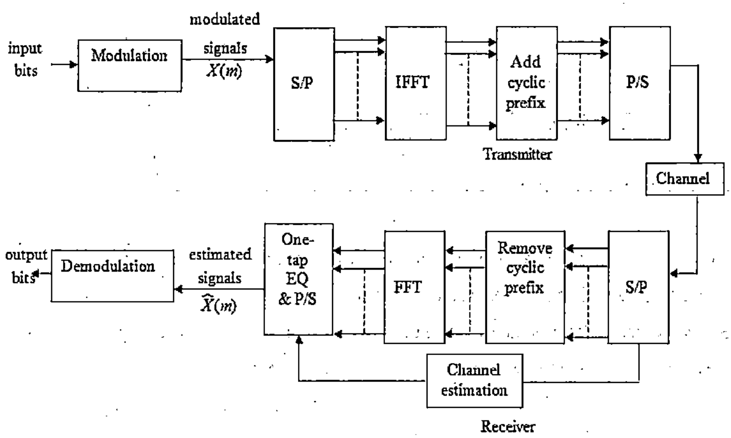


Figure 2.1.Base-band OFDM system model

Figure 2.1 shows a base-band equivalent representation of an OFDM system. The input binary data is first modulated using MPSK or MQAM. Schemes can vary from one sub-carrier to another in order to achieve the maximum capacity or the minimum bit error rate (BER). The modulated data symbols are represented by complex variables $\underline{X} = [X(0),....,X(M-1)]^T$. Modulated data symbols are then fed into a serial to parallel (S/P) converter. These data symbols are then transformed by the inverse fast Fourier transform (IFFT). The output symbols are denoted as $x(0),\dots\dots\dots x(M-1)$ [5].

Cyclic prefix (CP) symbols, which replicate the end part of the IFFT output symbols, are added in front of each frame to avoid ISI. The parallel data are converted back to a serial data stream before being transmitted over the frequency selective channel. The received data $y(0),\dots\dots\dots y(M-1)$ is corrupted by multipath fading and AWGN. The received data are converted back to $Y(0),\dots,Y(M-1)$ after discarding the prefix, and applying FFT and demodulation.

Let $\underline{H}$, $\underline{h}$, $\underline{N}$ denote the vectors of frequency-domain CIR, time-domain CIR, and additive white Gaussian noise respectively, where $\underline{h}=[h_0,\dots,h_{L-1}]^T$, $\underline{N}=[N(0),\dots,N(M-1)]^T$ and $\underline{H}=\mathbf{W}\underline{h}$, $\mathbf{W}$ is a $M\times L$ matrix:

$$\mathbf{W}=\begin{bmatrix} 1 & 1 & \cdots & 1 \\ 1 & e^{-j2\pi\frac{1}{M}} & \cdots & e^{-j2\pi\frac{L-1}{M}} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & e^{-j2\pi\frac{M-1}{M}} & \cdots & e^{-j2\pi\frac{(M-1)(L-1)}{M}} \end{bmatrix}_{M\times L} \tag{2.1}$$

The channel is modeled as a multipath time-invariant fading channel, which can be described by

$$y(k)=\sum_{l=0}^{L-1} h_l x(k-l)+n(k), \quad 0\le k\le M-1, \tag{2.2}$$

where h_l 's ($0\le l\le L-1$) are independent complex-valued Gaussian random variables, and n_k 's ($0 \le k \le M-1$) are independent complex-valued Gaussian random variables with zero mean and variance σ^2. L is the length of the time-domain CIR. Cyclic prefix (CP) is added in each OFDM data frame. In order to avoid ISI, the length of the cyclic prefix (CP) must be longer than L. Only one OFDM frame with M sub-carriers is considered in analyzing the system performance. After discarding the cyclic prefix and performing an FFT at the receiver, we can obtain the received data frame in the frequency domain:

$$Y(m)=\frac{1}{\sqrt{M}}\sum_{k=0}^{M-1}y(k)e^{-j2\pi\frac{km}{M}} \tag{2.3}$$

Substituting (2.2) in (2.3), we get

$$Y(m)=X(m)H(m)+N(m),\ 0\le m\le M-1 \tag{2.4}$$

where $H(m)$ is the frequency response of the channel at subcarrier m, which can be obtained by

$$H(m)=\sum_{l=0}^{L-1}h_l e^{-j2\pi\frac{ml}{M}},\ 0\le m\le M-1 \tag{2.5}$$

and the set of the transformed noise variables $N(m)$, $0\le m\le M-1$, which can be obtained by

$$N(m)=\frac{1}{\sqrt{M}}\sum_{k=0}^{M-1}n(k)e^{-j2\pi\frac{mk}{M}},\ 0\le m\le M-1 \tag{2.6}$$

are i.i.d. complex-valued Gaussian variables and have the same distribution as $n(k)$, i.e., with mean zero and variance σ^2.

2.2. Channel Estimation for OFDM systems

Channel estimation has significant role in single carrier communication systems [6, 7]. In these systems, the CIR is typically modeled as an unknown time-varying FIR filter, whose coefficients need to be estimated. In OFDM based systems, the data is modulated onto the orthogonal frequency carriers. For coherent detection of the transmitted data, these sub-channel frequency responses must be estimated and removed from the frequency samples. Like in single carrier systems, the time domain channel can be modeled as a FIR filter, where the delays and coefficients can be estimated from time domain received samples, which are then transformed to frequency domain for obtaining the channel frequency response (CFR). Alternatively, radio channel can also be estimated in frequency domain using the known (or detected) data on frequency domain sub-channels. Instead of estimating FIR coefficients, one tap CFR can be estimated (Figure 2.2).

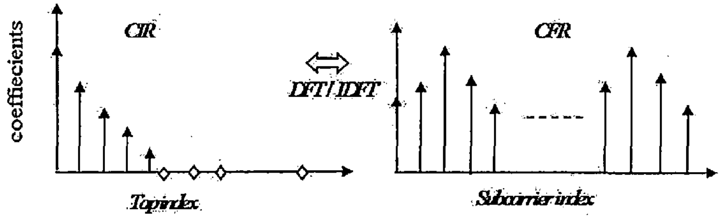


Figure 2.2. Time and frequency domain channel representation for OFDM systems

Channel estimation techniques for OFDM based systems can be grouped into two main categories: blind and non-blind. The blind channel estimation methods exploit the statistical behavior of the received signals and require a large amount of data. Hence, they suffer severe performance degradation in fast fading channels. On the other hand, in the non-blind channel estimation methods, information of previous channel estimates or some portion of the transmitted signal are available to the receiver to be used for the channel estimation. The non-blind channel estimation can be divided into two main groups: data aided and decision directed (DDCE).

In data aided channel estimation, a complete OFDM symbol or a portion of a symbol, which is known to the receiver, is transmitted so that the receiver can easily estimate the radio channel by demodulating the received samples. The estimation accuracy can be improved by increasing the pilot density. However, this introduces overhead and reduces the spectral efficiency. In the limiting case, pilot tones are assigned to all subcarriers of a particular OFDM symbol. This type of pilot arrangement is usually considered for slow channel variation and for burst type data transmission schemes, where the channel is assumed to be constant over the burst. The training symbols are then inserted at the beginning of the bursts to estimate the CFR.

In the DDCE methods, to decode the current OFDM symbol the channel estimates for a previous OFDM symbol are used. The channel corresponding to the current symbol is then estimated by using the newly estimated symbol information. Since an outdated channel is used in the decoding process, these estimates are less reliable as the channel can vary drastically from symbol to symbol. Hence, additional information is usually incorporated in DDCE such as periodically sent training symbols. Channel coding, interleaving, and iterative type approaches are also commonly applied to boost the performance of DDCE techniques.

Hence, the methods employed in data-aided and decision directed channel estimation need to be modified so that the variation of the channel over the OFDM symbol is taken into account for better estimates. There are basically three basic blocks affecting the performance of the non-blind channel estimation techniques. These are the pilot patterns, the estimation method, and the signal detection part.

Iterative channel estimation algorithms can be exploited to minimize the channel estimation errors. In these approaches, the channel estimation can be found via any of the methods described above, and the estimates can be improved using the detected signals. For iterative estimation, better performance is achieved at the expense of more computation [8].

2.2.1. Expectation-Maximization Algorithm

The Expectation-Maximization (EM) algorithm is a technique for finding maximum likelihood estimates of system parameters in a broad range of problems where observed data are incomplete. The EM algorithm consists of two major steps: an expectation step, followed by a maximization step. The expectation is with respect to the unknown underlying variables, using the current estimate of the parameters and conditioned upon observations. The maximization step then provides a new estimate of the parameters. These two steps are iterated until the estimated values converge [9, 10].

Consider θ as a set of deterministic channel parameters to be estimated from the observed data Y={y(0),.........,y(M-1)}, ML estimation of θ is given by, $\hat{\theta} = \arg\max_{\theta}\{f(Y/\theta)\}$ .when Y has insufficient information (incomplete data), the maximization of $f(Y/\theta)$ is not tractable and does not lead to an explicit expression .

We assume that the data Z ("complete" data) can be separated into two components, Z=(Y, I), where Y is the observed data ("incomplete" data) and I is the missing data

The E-step compute the expected value of the Z (complete data) using the current estimate of the parameter $\theta^{(k)}$ and observed data Y.

For the E-step compute:

$$Q(\theta / \theta^{(k)}) = E\{\log f(Z / \theta) / Y = y, \theta^k\} \tag{2.7}$$

The M-step then finds $\theta^{(k+1)}$, the value of θ that maximizes $Q(\theta / \theta^{(k)})$ over all possible values of θ:

$$\theta^{(k+1)} = \arg\max_{\theta} Q(\theta / \theta^{(k)}) \tag{2.8}$$

This procedure is repeated until the sequence $\theta^{(0)}, \theta^{(1)}, \theta^{(2)}, ...$ converges. The EM algorithm is constructed in such a way that the sequence of $\theta^{(k)}$'s converges to the ML estimate of θ.

2.2.2. Channel estimation for OFDM using EM algorithm

OFDM divides its allocated channel spectrum into several parallel sub channels that are only subjected to flat fading. Thus we only need to estimate the individual $H(m)$, $0 \le m \le M-1$, separately, which will result in a considerable reduction in computational complexity. To simplify the expressions, we omit the subcarrier index m, and simply write Y, X, and H instead of $Y(m)$, $X(m)$, and $H(m)$ [5,11].

We assume that the frequency-domain signal X of a given subcarrier represents a QPSK or QAM signal with constellation size C (=4 or 16 respectively).we denote the symbols in the signal constellation by $\{X_i, 1 \le i \le C\}$.

Due to Gaussian noise assumption, the probability density function (pdf) of Y given X and H given by

$$f(Y / X, H) = \frac{1}{2\pi\sigma^2} \exp\left\{-\frac{1}{2\sigma^2}|Y - HX|^2\right\} \tag{2.9}$$

By Assuming that all C symbols are equally likely and averaging the conditional pdf of (2.9) over the variable X, we obtain the pdf of Y given H as follows:

$$f(Y / H) = \sum_{i=1}^{C} \frac{1}{2\pi\sigma^2 C} \exp\left\{-\frac{1}{2\sigma^2}|Y - HX_i|^2\right\} \tag{2.10}$$

Suppose the channel is static over the period of D OFDM frames. Different values of D can be applied in different applications depending on how rapidly the channel changes. We define the received signal vector $\underline{Y}=\left[Y^1,\ldots,Y^D\right]$ and the transmitted signal vector $\underline{X}=\left[X^1,\ldots X^D\right]$ for a specific subcarrier over D frames. Then we call $\underline{Y}$ and $(\underline{Y},\underline{X})$ "incomplete" and "complete" data, respectively. Assuming that additive Gaussian noise is independent from frame to frame for each subcarrier, the conditional pdf of the incomplete data can be written as follows:

$$f(\underline{Y}/H,\underline{X})=\prod_{d=1}^{D} f\left(Y^d/H,X^d\right), \tag{2.11}$$

Thus, the log–likelihood function of the incomplete data is

$$\log f(\underline{Y}/H,\underline{X})=\sum_{d=1}^{D}\log f\left(Y^d/H,X^d\right), \tag{2.12}$$

And the log-likelihood function of the complete data is given by

$$\log f(\underline{Y}/H,\underline{X})=\sum_{d=1}^{D}\log\left\{\frac{1}{C}f\left(Y^d/H,X_i\right)\right\}, \tag{2.13}$$

Each iterative process p=0,1,2,....in the EM algorithm for estimating H from $\underline{Y}$ consists of the following two steps:

E-step:

$$Q\left(H/H^{(p)}\right)=E_{\underline{X}}\left\{\log f(\underline{Y},\underline{X}/H)/\underline{Y},H^{(p)}\right\} \tag{2.14}$$

M-step:

$$\tilde{H}^{(p+1)}=\arg\max_{H} Q\left(H/H^{(p)}\right), \tag{2.15}$$

where

$$Q\left(H/H^{(p)}\right)=\sum_{i=1}^{C}\sum_{d=1}^{D}\log\left\{\frac{1}{C}f\left(Y^d/H,X_i\right)\right\}\frac{f\left(Y^d/H^{(p)},X_i\right)}{C f\left(Y^d/H^{(p)}\right)} \tag{2.16}$$

$\tilde{H}^{(p+1)}$ is the tentative estimate of H directly from (2.15). The final (p+1)st estimate of H , that is, $H^{(p+1)}$, will be obtained through additional manipulation on $\tilde{H}^{(p+1)}$.

The value of H that maximizes (2.16) is found as follows:

$$\tilde{H}^{(p+1)} = \left[\sum_{i=1}^{C} \sum_{d=1}^{D} |X_i|^2 \frac{f\left(Y^d / H^{(p)}, X_i\right)}{f\left(Y^d / H^{(p)}\right)} \right]^{-1} \times \left[\sum_{i=1}^{C} \sum_{d=1}^{D} Y^d X_i^* \frac{f\left(Y^d / H^{(p)}, X_i\right)}{f\left(Y^d / H^{(p)}\right)} \right] \quad (2.17)$$

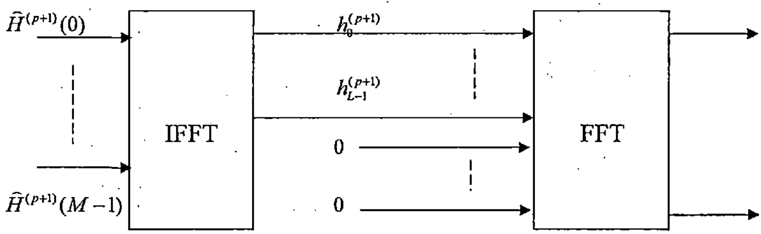


Figure 2.3. Low pass filter structure

Channel is estimated in frequency domain at each iteration and then IFFT is computed to convert it into time domain that has M paths. In those M paths only L are relevant, all other are made as zero and again FFT is computed as shown in figure 2.3.

In each iteration, the updated estimate of channel impulse response $\underline{\hat{h}}^{(p)}$ is obtained automatically as a byproduct. It is assumed that the number of multipaths L is known. In a real situation, L may not be known. In such a case, channel-order detection together with parameter estimation has to be done. Alternatively, we may use some upper bound for L, which may be easier to obtain than trying to estimate an exact value of L. In an OFDM system L can be set equal to or less than the length of the cyclic prefix. Another limitation of this model is that the mean $E\{\underline{h}\}$ and the covariance matrix Σ of time-domain CIR are also assumed to be known. In a practical situation, these channel statistics may not be known.

From the general convergence property of the EM algorithm, there is no guarantee that the iterative steps converge to a global maximum. For a likelihood function with multiple local maxima the convergence point may be one of these local maxima, depending on the initial estimate $\underline{H}^{(0)}$. So, pilot symbols are used to obtain an appropriate initial value $\underline{H}^{(0)}$, which is more likely to converge to the true maximum point.

2.2.3. Channel estimation for OFDM systems using EM-MMSE algorithm

From equation (2.7), it may be seen that expectation of cost function (Q) is taken over all possible values of unknown parameters. The EM technique has the advantage of being simple in principle but computing the expectations and performing the maximizations may be computationally taxing. In conventional EM-based techniques for estimating the channel parameters in OFDM systems, a cost function is defined in terms of received signal, channel information and transmitted signal. Transmitted signal and channel information is unknown at the receiver. In E-step of EM technique, averaging of cost function is done on all possible values of transmitted data. Then in M-step, the estimated cost function is maximized to estimate the channel parameters. This process is done iteratively until convergence [12].

In conventional EM technique we estimate the cost function for all possible values of transmitted symbol. But in EM-MMSE, at each iteration, we first find the transmitted sequence using the knowledge of channel at that iteration. The transmitted sequence is calculated using MMSE method in step A.

Step A:

First $\left\|Y(m) - H^{(p)}(m)X_i(m)\right\|^2$ is calculated for $1 \le i \le C$, for each carrier and the transmitted sequence is calculated at p^{th} iteration using MMSE. Let this estimate of the transmitted sequence for each frame at iteration p is represented by $\hat{\underline{X}}^{(p)}$. Equation (2.4) can be represented in vector form for each frame,

$$\underline{Y} = \underline{H} \bullet \underline{X} + \underline{N} \tag{2.18}$$

Where $\bullet$ operator denotes Hadamard product (element-wise matrix multiplication and both matrices must have the same dimension) and $\underline{H}$ is the channel frequency response vector of dimension $1 \times M$.

Log Likelihood (cost function) for OFDM system in vector form for a frame can be defined as $f(\underline{Y}, \underline{X} / \underline{H})$.

EM-MMSE can be directly applied for each frame,

At $(p+1)^{th}$ iteration,

E-step:

$$Q(\underline{H} / \underline{\hat{H}}^{(p)}) = \mathbf{E}_X \left[\log f(\underline{Y}, \underline{X} / \underline{H}) / \underline{Y}, \underline{\hat{H}}^{(p)} \right] \tag{2.19}$$

where expectation is calculated using the received symbol and channel estimate at p^{th} iteration.

After taking expectation on estimated transmitted sequence $\underline{\hat{X}}^{(p)}$.

$$Q(\underline{H} / \underline{\hat{H}}^{(p)}) = \left[\log f(\underline{Y}, \underline{\hat{X}}^{(p)} / \underline{H}) / \underline{Y}, \underline{\hat{H}}^{(p)} \right] \tag{2.20}$$

M-step:

Maximizing the Q function of (8), we will get,

$$\underline{\hat{H}}^{(p+1)} = \left[\underline{\hat{X}}^{(p)} \bullet \underline{\hat{X}}^{(p)^*} \right]^{-1} \times \left[\underline{Y} \bullet \underline{\hat{X}}^{(p)^*} \right] \tag{2.21}$$

Using step A and (2.21), iteratively, channel is estimated in frequency domain. IFFT is computed to convert it into time domain channel that has M paths. Since only L paths are relevant, all other paths are made zero and again FFT is computed. For initial estimation of $\underline{\hat{H}}^{(0)}$, pilot based technique with linear interpolation is used.

The efficiency of a channel estimator may be judged by the amount of training required and the computational complexity involved. In EM-MMSE algorithm, computational complexity is reduced and it requires less number of pilot symbols as initial estimation is done only once.

2.3. Simulation results

The channel estimation algorithm is tested through Monte Carlo simulations. We consider a 128 subcarrier OFDM system, with QPSK as the underlying modulation scheme. A Rayleigh multipath fading channel model with both stationary and time varying environment are considered and time varying environment is characterized by AR2 channel model. An operating frequency of 2 GHz and a channel bandwidth of 2048 KHz have been assumed. The channel is assumed to be quasi static and does not vary with in each frame. For Rayleigh stationary multipath fading, channel has been assumed independent for each OFDM frame and for time selective multipath fading, channel varies for each frame according to Doppler values. . Each frame consists of 30 symbols. We have taken Doppler values of f_dT=0.005, f_dT=0.01, f_dT=0.001 and f_dT=0.05 [12]. Simulation has been done in MATLAB environment. The system performance is evaluated for SNR values of 0-30db by averaging over 1000 frames.

Rayleigh stationary multipath fading channel model:

The impulse response h (n) of the stationary multipath fading channel can be modeled as,

$$h(n) = \frac{1}{K}\sum_{k=0}^{L} e^{-k/2}\alpha_k \delta(n-k)$$

Where $K = \sqrt{\sum_{k=0}^{L} e^{-k}}$ is the normalization constant and $\alpha_k, 0 \le k \le L$ are independent complex valued Gaussian distributed random variable.

This is the conventional exponential decay multipath model. We have used, 4 tap stationary multipath channel model as in [13],

$$h(n) = 0.806\alpha_0\delta(n) + 0.486\alpha_1\delta(n-1) + 0.2952\alpha_2\delta(n-2) + 0.179\alpha_3\delta(n-3) \quad (2.23)$$

Where, $\alpha_i, 0 \le i \le 3$ are independent complex valued Gaussian distributed random variables with zero mean and unit variance.

Time varying channel model using AR2 process:

Time selective channel is approximated by an independent autoregressive process of order-2 (AR2). The channel tap vector for each OFDM frame is denoted by $h_n = [h(n,0)\ h(n,1)\ h(n,2)\ h(n,3)]$, where $h(n,l)$ is the l^{th} tap for the n^{th} frame [14]. Considering the AR2 model,

$$h(n,l) = a_1 h(n-1,l) + a_2 h(n-2,l) + v(n,l) \tag{2.24}$$

Where a_1 and a_2 are the AR2 coefficients and $v(n,l)$ is the modeling noise for l^{th} tap at time frame n. the parameters a_1 and a_2 are closely related to the physical parameters of the underlying fading process. The values of AR2 coefficient can be obtained as,

$$a_1 = -2r_d \cos(2\pi f_p T)$$
$$a_2 = r_d^2 \tag{2.25}$$

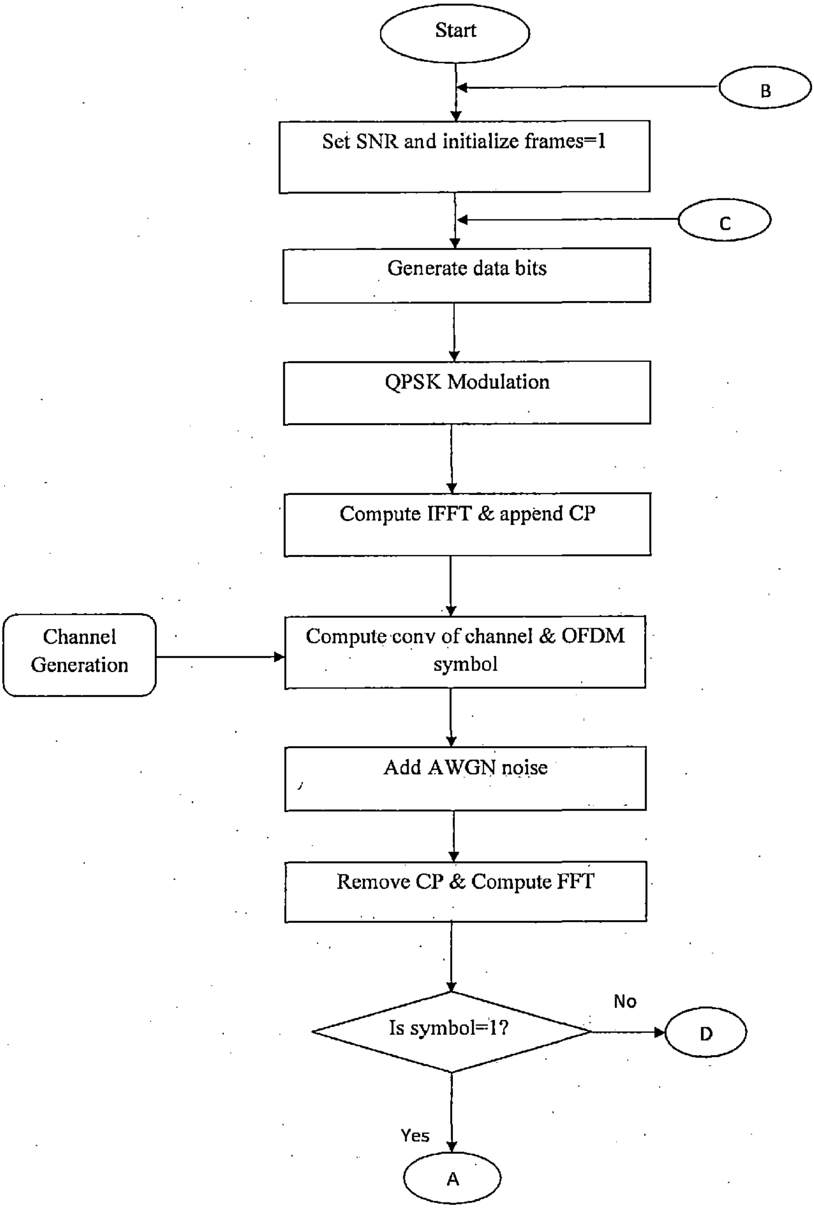
Where f_p is the spectral peak frequency, T is the symbol period, r_d is the pole radius that corresponds to the steepness of the peaks of power spectrum

i.e. $r_d = \left(1 - \frac{w_d}{\pi}\right)$ (2.26)

It has been observed in literature that when the spectral peak frequency $f_p = 0.8 f_d$ (f_d is the maximum Doppler frequency of the underlying fading channel), the autocorrelation function of AR2 process is close to the autocorrelation function of a fading process characterized by Bessel function. The variance of the fading coefficient $h(n,l)$ is decided by the variance of $v(n,l)$, which is given by

$$\sigma_c^2 = \left(\frac{1+a_2}{1+a_1}\right) \frac{\sigma_w^2}{\left[(1+a_2)^2 - a_1^2\right]} \tag{2.27}$$

Figure 2.4. shows the flow chart of simulation structure of SISO-OFDM systems. We first initialize the system parameters. Channel is modeled using Rayleigh multipath fading with both stationary and time varying environment. Time varying environment is characterized by AR2 channel model.


Start
B
Set SNR and initialize frames=1
C
Generate data bits
QPSK Modulation
Compute IFFT & append CP
Channel Generation
Compute conv of channel & OFDM symbol
Add AWGN noise
Remove CP & Compute FFT
Is symbol=1?
No
D
Yes
A

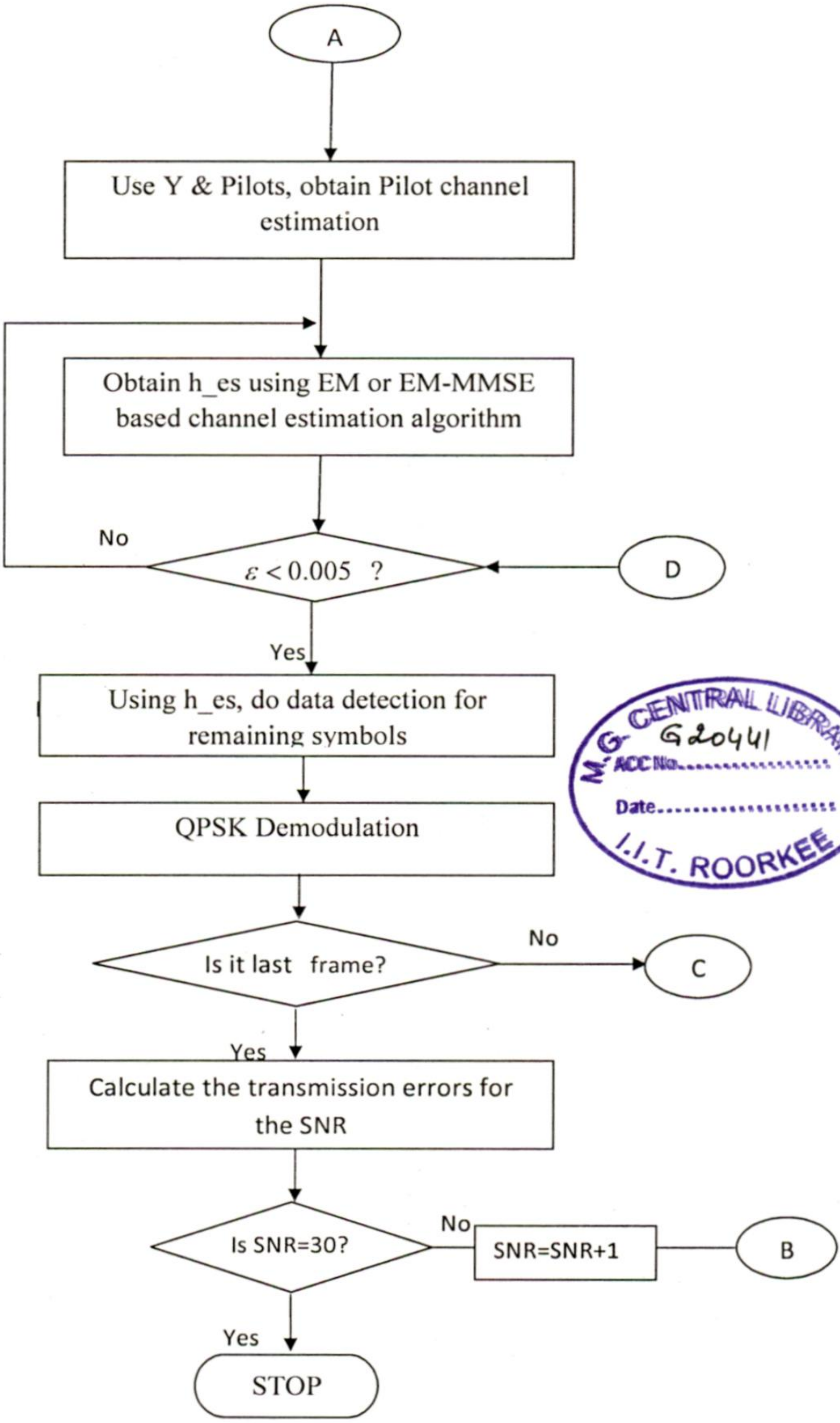


Figure 2.4. Flow chart for simulation of OFDM system

Figure2.5 and figure 2.6 shows the performance curves for the EM , EM-MMSE and pilot based estimators for OFDM systems in Rayleigh fading environment.The BER performance obtained when exact channel state information(CSI) is known is also plotted for comparison.We generate 100 independent realizations of the channel at each value of SNR for averaging. Pilot based estimator using 4 pilots achieves a BER of 0.013 at SNR of 30dB . It can also be seen that EM & EM-MMSE techniques also achieves a BER of 0.0017 at SNR of 30dB . The performance improves to within 0.3 dB of exact CSI curve at high SNRs. Figure 2.6 compares the average number of iterations required using the EM & EM-MMSE techniques for channel estimation in Rayleigh fading environment for OFDM systems. It may be seen that the number of iterations required for EM-MMSE technique is reduced by a factor of almost 6 as compared to EM method.

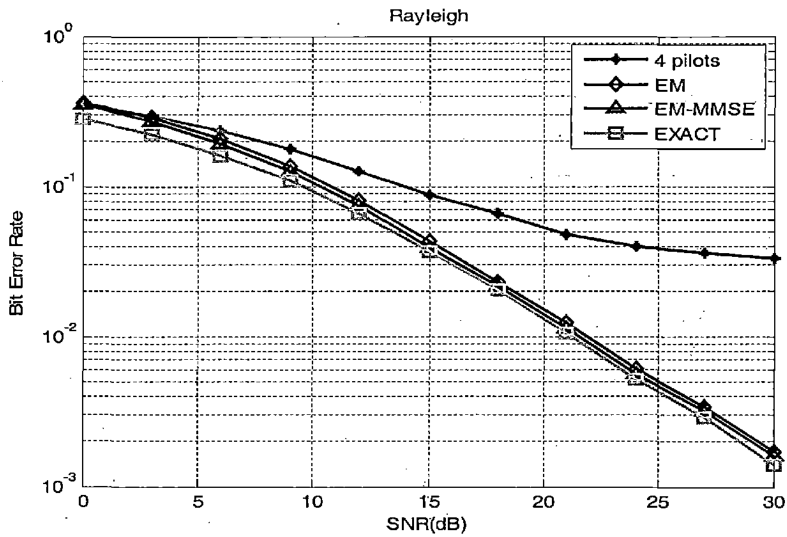


Figure 2.5 Comparison of BER performance for EM , EM-MMSE and pilot based channel estimation techniques in Rayleigh fading environment for OFDM systems

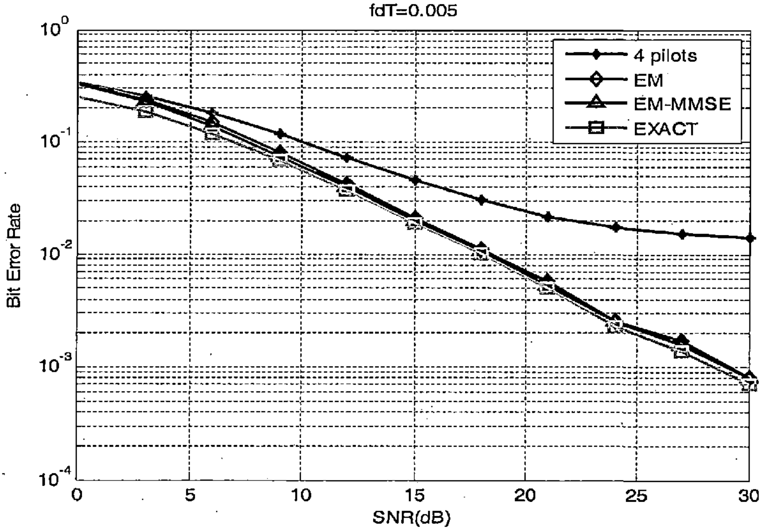


Figure 2.7 Comparison of BER performance for EM , EM-MMSE and pilot based channel estimation techniques in time varying fading environment for OFDM systems(f_dT =0.005).

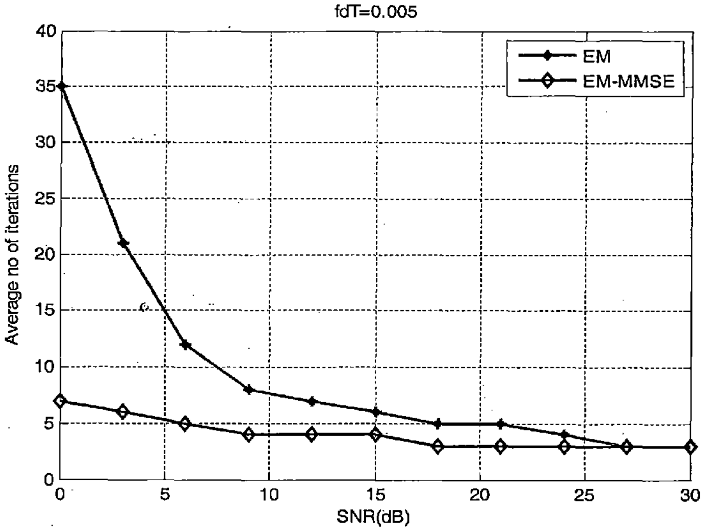


Figure 2.8 Comparison of average number of iterations for EM and EM-MMSE based channel estimation techniques in time varying fading environment for OFDM systems($f_d T$ =0.005).

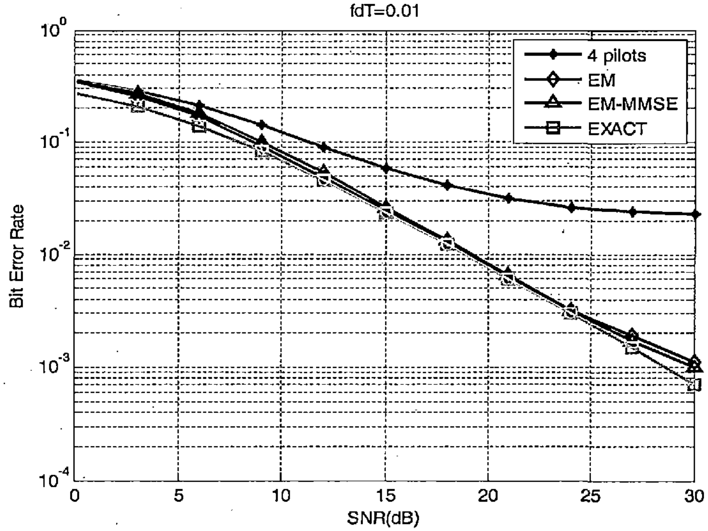


Figure 2.9 Comparison of BER performance for EM , EM-MMSE and pilot based channel estimation techniques in time varying fading environment for OFDM systems($f_d T$=0.01).

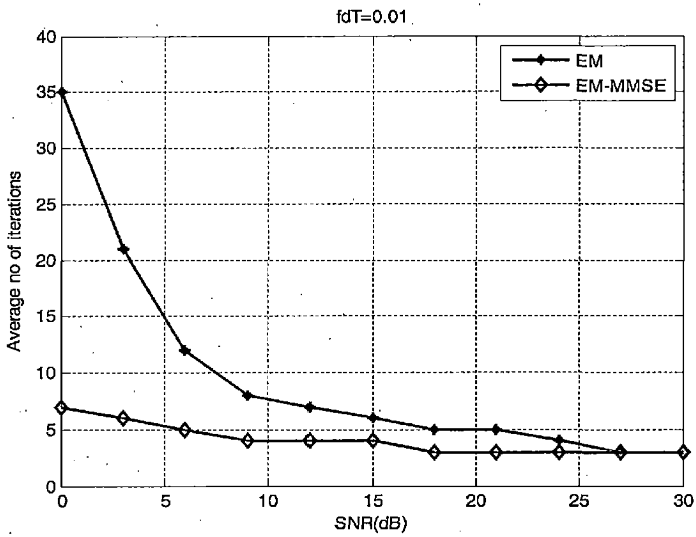


Figure 2.10 Comparison of average number of iterations for EM and EM-MMSE based channel estimation techniques in time varying fading environment for OFDM systems(f_dT=0.01).

The performance curves for the EM , EM-MMSE and pilot based estimators for OFDM systems in time varying fading environment for doppler values of f_dT=0.001 and f_dT=0.05 are shown below. Pilot based estimator using 4 pilots achieves a BER of 0.0283 at SNR of 30dB for f_dT=0.001 and achieves a BER of 0.023 at SNR of 30dB for f_dT=0.05. It can also be seen that EM& EM-MMSE techniques also achieves a BER of 0.0002 at SNR of 30dB for f_dT=0.001 and achieves a BER of 0.0012 at SNR of 30dB for f_dT=0.05. Fig 2.12 & 2.14 compare the average number of iterations required for EM & EM-MMSE techniques for channel estimation in time varying fading environment for OFDM systems. It may be seen that the number of iterations required for EM-MMSE technique is reduced by a factor of almost 6 as compared to EM method.

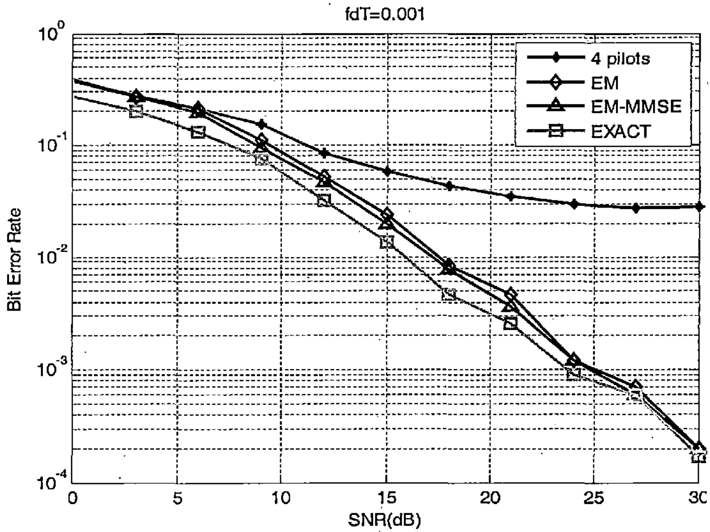


Figure 2.11 Comparison of BER performance for EM , EM-MMSE and pilot based channel estimation techniques in time varying fading environment for OFDM systems(f_dT =0.001).

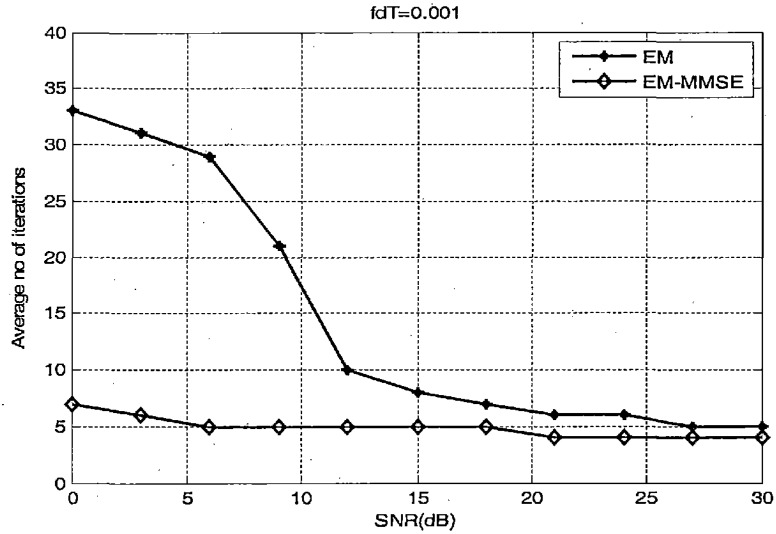


Figure 2.12 Comparison of average number of iterations for EM and EM-MMSE based channel estimation techniques in time varying fading environment for OFDM systems($f_d T$=0.001).

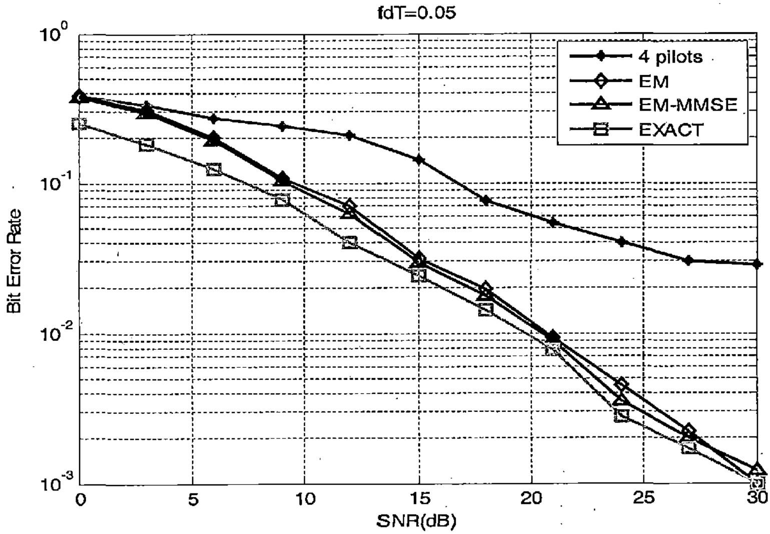


Figure 2.13 Comparison of BER performance for EM , EM-MMSE and pilot based channel estimation techniques in time varying fading environment for OFDM systems(f_dT=0.05).

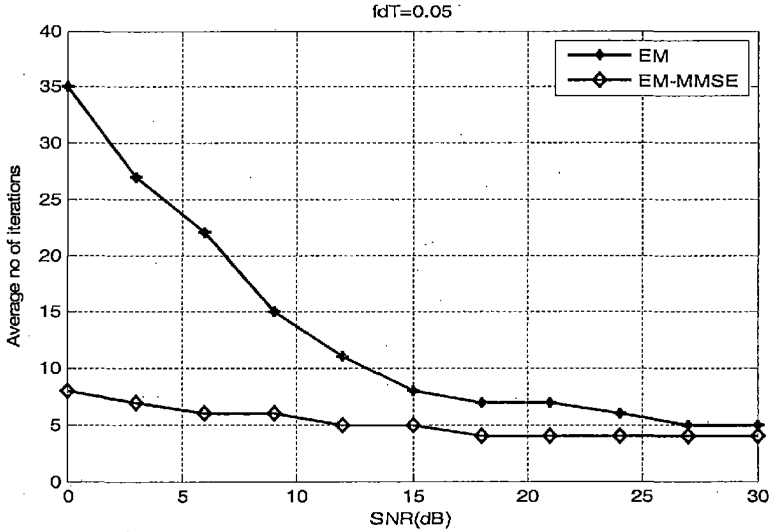


Figure 2.14 Comparison of average number of iterations for EM and EM-MMSE based channel estimation techniques in time varying fading environment for OFDM systems($f_d T$ =0.05).

Chapter 3
EM BASED CHANNEL ESTIMATION FOR MIMO-OFDM SYSTEMS

In this chapter, VBLAST detection algorithm is described first. Next, BICM MIMO-OFDM system model is described. Conventional EM and hard VBLAST-EM based channel estimation for MIMO-OFDM systems are discussed next. Simulation results on the performance of hard VBLAST-EM based channel estimation for MIMO-OFDM systems are presented at the end.

Kashima et al. in [15] have proposed two types of maximum a posteriori probability (MAP) receivers for multiple-input–multiple-output and orthogonal frequency-division multiplexing mobile communications with a low-density parity-check (LDPC) code. First proposed receiver employs the expectation-maximization algorithm so as to improve performance of approximated MAP detection. Different from a conventional receiver employing the minimum mean-square estimation (MMSE) algorithm, it applies the recursive least squares (RLS) algorithm to the channel estimation in order to track a fast fading channel. It not only improves the accuracy of the channel estimation but also can save the computational complexity. This is because the RLS is a recursive algorithm whereas the MMSE is a block type. The proposed receiver estimation is superior in channel-tracking ability to the conventional receiver employing the MMSE.

In [16], iterative channel estimators for MIMO systems based on the expectation-maximization (EM) algorithm are proposed. A major problem with the EM channel-tap estimation is that the estimates are biased. This bias can severely degrade the receiver performance. The authors have proposed an unbiased EM (UEM) channel estimator, which outperforms the classical EM estimator. The EM and UEM estimators require a matrix inversion. In order to avoid this matrix inversion, and thus to reduce the estimator complexity, the expectation-conditional-maximization (ECM) algorithm is proposed. This decreases the complexity of the maximization step of the iterative estimation process. Like the EM algorithm, the ECM algorithm leads to a biased channel-tap estimate. An unbiased

ECM (UECM) estimator has also been proposed. These algorithms have been applied for a turbo receiver operating over frequency-selective multiple-input multiple-output channels in order to compare them with known estimators, like the EM and the classical DA ML(decision aided ML) and DD-ML (decision directed ML) criterion. The iterative CIR (channel impulse response) estimation techniques outperform the classical DA ML (decision aided maximum likelihood) channel estimator.

In [17], the authors have derived an iterative receiver for multiple-input multiple-output orthogonal frequency division multiplexing (MIMO-OFDM) systems. The iterative receiver is investigated when the co-channel interference (CCI) exists. It is assumed that the CCI's are also OFDM signals. Since a joint detection of the desired signal and CCI is difficult, the desired signal is detected, while the CCI is assumed to be a (colored) noise. This approach can avoid the channel estimation and detection of the CCI and keep the complexity of the receiver low. The proposed iterative receiver estimates the channel impulse response of the desired signal and the covariance matrix of the CCI for the detection based on a generalized expectation maximization (GEM) algorithm. Since the CCI is considered as a noise in the GEM-based iterative receiver, the performance is limited by the CCI. Through GEM iterations, the performance is improved.

Mohammad-Ali Khalighi et al. [18] have considered channel estimation in multiple-input multiple-output (MIMO) systems using iterative detection at the receiver. Space-time bit-interleaved coded modulation (BICM) and soft-input soft-output maximum a posteriori (MAP) symbol detection and decoding are considered. The advantage of the BICM is its flexibility regarding the choice of the code and the bit-symbol mapping, as well as its conformity to iterative detection. The EM algorithm based on the maximum-likelihood (ML) criterion is used to update the channel coefficients at each iteration of the turbo-detector. At the first iteration, a primary channel estimate was obtained based on the pilot sequences only, that allows the EM algorithm to be used in the succeeding iterations, to bootstrap. A "classical" and non-optimized EM implementation, gives a biased estimate of the channel coefficients. The authors optimized the EM implementation and proposed a modification to it that provides an unbiased channel estimate and leads to a better convergence of the iterative detector. The proposed modified unbiased (MU) EM algorithms, especially for large number of transmit antennas and short training sequences achieved considerable improvement in the receiver performance. Finally the authors have considered a simple semi-blind estimation scheme, based on hard decisions on reliable decoded data bits, and compare its performance with the EM based estimation methods.

In [19], the authors have proposed an EM based algorithm to detect the transmitted V-BLAST structured signals in MIMO OFDM systems while estimating the channel impulse response (CIR) iteratively. The proposed iterative algorithm can jointly estimate channel information and detect the V-BLAST structured signals in MIMO OFDM system. This method combines the interference canceling techniques with the expectation maximization (EM) algorithm, which is a general procedure for iterative maximum-likelihood estimation.

In [20], an iterative channel estimation scheme for VBLAST MIMO OFDM system is proposed. The channel estimation is done in two steps. In first step, PSA (pilot symbol aided) method is used, to get the initial channel estimation of the systems. In second step, the information bits are feedback to the channel estimator with help of Turbo iterative decoding. EM algorithm is used for iterative channel estimation.

In [21], a convolutionally coded MIMO-OFDM system with EM-based channel estimation and a QRD-M data detection algorithm is considered. In this, one training symbol is transmitted from each transmit antenna for the MIMO channel estimation at the receiver. With the channel estimates available, data detection is done with QR decomposition and then makes the decisions from the strongest data to weakest data sequentially. M algorithm is combined to reduce the computational complexity.

Pilot-symbol assisted modulation (PSAM) schemes for channel estimation are popular in single input single output (SISO) systems due to their simplicity and minimum mean square error (MMSE) optimality. The iterative channel estimators (ICEs) have the drawback that the interference from other transmit antennas cannot be removed when applied to V-BLAST OFDM systems. An ICE for MPSK V-BLAST OFDM systems operating on frequency-selective fading channels is proposed in [22]. The correlations that depend not only on the channel statistics but also on the a priori information of the transmitted symbols are considered. The proposed ICE is robust on fast fading channels and has an inherent interference cancelling ability and it significantly improves the bit error rate (BER) performance when compared to conventional non-iterative PSAM estimators. The computational complexity of the proposed ICE is significantly greater than that of PSAM techniques due to the required inversion of an autocorrelation matrix. Furthermore, unreliable a priori information from the channel decoder degrades the performance of the proposed ICE. Hence, the authors have proposed a low-complexity (LC)-ICE that exploits the most reliable a priori information in an efficient manner.

3.1. Vertical Bell Laboratories Space-Time Architecture (VBLAST)

Block diagram of high level V-BLAST system is shown in figure 3.1. A single data stream is demultiplexed into M sub-streams, and each sub-stream is then encoded into symbols and fed to its respective transmitter, where M is number of transmitters. All the transmitters operate co-channel at symbol rate $1/T$ symbols/sec, with synchronized symbol timing. Each transmitter is an ordinary QAM transmitter. The collection of transmitters comprises a vector-valued transmitter, where components of each transmitted M-vector are the symbols drawn from a QAM constellation. V-BLAST is a vector encoding process (a demultiplex operation followed by independent bit-to-symbol mapping of each sub-stream).Receivers (1to N) are, individually, ordinary QAM receivers. These receivers also operate co channel, each receiving the signals radiated from all M transmit antennas [23].

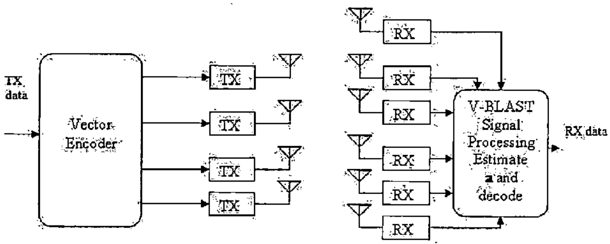


Figure 3.1. V-BLAST high level system diagram

V-BLAST is essentially a single-user system which uses multiple transmitters. BLAST is simply using traditional multiple access techniques in a single-user fashion, i.e.

$$\mathbf{r}_2 = \mathbf{r}_1 - \hat{a}_{k_1}(\mathbf{H})_{k_1} \tag{3.3}$$

where $(\mathbf{H})_{k_1}$ denotes the k_1th column of $\mathbf{H}$. Steps 1-3 are then performed for components $k_2, \ldots k_M$ by taking $\mathbf{r}_2, \mathbf{r}_3, \ldots\ldots, \mathbf{r}_M$ respectively. The specifics of the detection process depend on the criterion chosen to compute the nulling vectors w_{k_1}, the most commonly minimum mean-squared error (MMSE) and zero-forcing (ZF) are used.

The k_ith ZF nulling vector is defined as the minimum norm vector satisfying

$$w_{k_i}^T(\mathbf{H})_{k_i} = \begin{cases} 0 & j > i \\ 1 & j = i \end{cases} \tag{3.4}$$

Thus, the k_ith ZF-nulling vector is orthogonal to the subspace spanned by the contributions to $\mathbf{r}_i$ due to those symbols not yet estimated and cancelled. It is not difficult to show that the unique vector satisfying equation. (3.4) is just the k_ith row of $\mathbf{H}_{k_{j-1}}^{\dagger}$, where the notation $\mathbf{H}_{k_i}^{\dagger}$ denotes the matrix obtained by zeroing columns k_1, $k_2, \ldots, k_i$ of $\mathbf{H}$ and † denotes the Moore-Penrose pseudo inverse.

The ordered successive cancellation (OSUC) is combined with the MMSE algorithm to suppresses both the interference and noise components, where as ZF removes only the interference components. This implies that the mean square error between the transmitted symbols and the estimate of the receiver is minimized [25].

3.2. BICM MIMO-OFDM system Model [26]

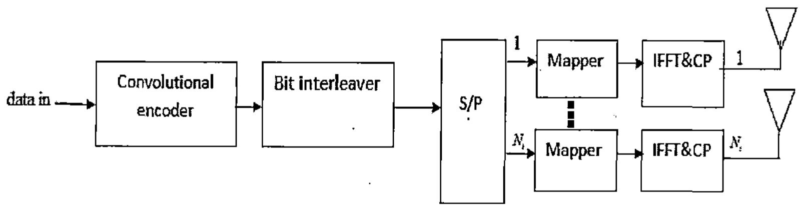


Figure 3.2(a) BICM MIMO-OFDM transmitter

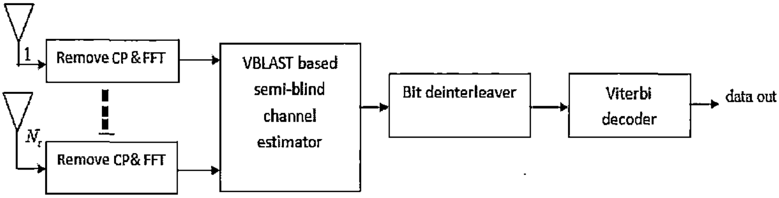


Figure 3.2(b) BICM MIMO-OFDM receiver

A convolutionally coded layered MIMO OFDM system with N_t transmit antennas, N_r receive antennas and N useful subcarriers as shown in figure 3.2(a) is considered in [26]. The input bits are convolutionally encoded, bit-interleaved. The bit-interleaved bit stream is passed through S/P (serial to parallel converter) to convert it into parallel stream. The parallel stream is mapped onto symbols from the constellation. The modulated symbols are passed through IFFT and transmitted via antennas after concatenation of cyclic prefix (CP). Since size constraints on user-end equipment may not permit proper antenna separation, paths between antennas are assumed to be dependent. Multipath fading is modeled as a tapped delay line (TDL) with L taps, $\mathbf{h}^{q,p}$ denoting the $L\times 1$, channel tap vector from pth transmit to qth receive antenna.

The frequency response of the channel between the pth transmit and the qth receive antenna may be expressed as

$$H^{q,p}(k)=\frac{1}{\sqrt{N}}\sum_{l=0}^{L-1}h^{q,p}(l)e^{-j2\pi kl/N},0\le k\le N-1 \tag{3.5}$$

Taking DFT at the q^{th} receive antenna, the received signal at sub carrier k becomes

$$Y^{q}(k)=\sum_{p=1}^{N_t}H^{q,p}(k)X^{p}(k)+W^{q}(k),1\le q\le N_r \tag{3.6}$$

where $X^{p}(k)$ is the symbol transmitted from antenna p at subcarrier k.

An alternative representation of the received symbols is as follows:

$$\mathbf{y}(k)=\mathbf{H}(k)\mathbf{x}(k)+\mathbf{w}(k) \tag{3.7}$$

Where $\mathbf{y}(k)$ is the $N_r \times 1$ received signal vector on subcarrier, $\mathbf{x}(k)$ is the $N_t \times 1$ transmit vector and $\mathbf{H}(k)$ is the $N_r \times N_t$ matrix whose $(p,q)^{th}$ element is the frequency response of the channel from transmit antenna q to receive antenna p at subcarrier k, given by $H^{p,q}(k)$ and may be obtained from (3.5) by reversal of variables.

The conventional VBLAST detection algorithm for MIMO-OFDM systems is a simple approach capable of attaining high spectral efficiency. The VBLAST algorithm at receiver based on [24] has been used for estimation of data as shown in figure 3.2(b). These data bits are bit interleaved and Viterbi decoded to get the estimate of transmitted data bits.

3.3. Channel Estimation for MIMO-OFDM

Assuming P pilots in an OFDM symbol and gathering the received pilots at q^{th} antenna, then

$$\tilde{\mathbf{Y}}^q=\tilde{\mathbf{A}}\mathbf{h}^q+\tilde{\mathbf{W}}^q \tag{3.8}$$

Where $\mathbf{h}^q$ is the $LN_t \times 1$ vector of the channel taps from all transmit antennas to the q^{th} receive antenna, $\tilde{\mathbf{W}}^q$ consists of P AWGN noise samples with zero mean and identical variance σ_w^2 and

$$\tilde{\mathbf{A}}=[diag(X^1(k_1),....X^1(k_P))\tilde{\mathbf{F}}_L.....diag(X^{N_t}(k_1),....X^{N_t}(k_P))\tilde{\mathbf{F}}_L]_{P\times LN_t} \tag{3.9}$$

And $\tilde{\mathbf{F}}_L$ is a P×L matrix obtained from the standard N×N DFT matrix. The least squares (LS) solution is obtained as

$$\hat{\mathbf{h}}^q=\tilde{\mathbf{A}}^{-1}\tilde{\mathbf{Y}}^q \tag{3.10}$$

This pilot aided channel estimation method is also known as PACE.

3.3.1. Semi-blind channel estimation based on conventional EM:

Considering (3.6) and (3.7), the received sequence for all the tones, we get

$$\mathbf{Y}^q = \mathbf{A}\mathbf{h}^q + \mathbf{W}^q \tag{3.11}$$

where $\mathbf{Y}^q$ is the $N \times 1$ vector received on antenna q and

$$\mathbf{A} = [diag(X^1(k_1),....X^1(k_P))\mathbf{F}_L.....diag(X^{N_t}(k_1),....X^{N_t}(k_P))\mathbf{F}_L]_{N\times LN_t} \tag{3.12}$$

$\mathbf{X}^p$ is the $N \times 1$ transmit vector from antenna p and $\mathbf{F}_L$ has first L columns of DFT matrix.

Applying conventional EM to this system, we define the log-likelihood function of complete information as

$$L = \log f(\mathbf{Y}^q, \mathbf{A} / \mathbf{h}^q) \tag{3.13}$$

Since **A** is unknown, taking expectation then (3.13) becomes

$$L = E[\log f(\mathbf{Y}^q, \mathbf{A} / \mathbf{h}^q) / \mathbf{Y}^q, h_i^q]$$

$$= E[(\log f(\mathbf{Y}^q / \mathbf{A}, \mathbf{h}^q) f(\mathbf{A})) / \mathbf{Y}^q, h_i^q] \tag{3.14}$$

where **A** is assumed to be independent of the channel, h_i^q is the estimated vector of size $N \times 1$ step i. Thus

$$f(\mathbf{Y}^q / \mathbf{A}, \mathbf{h}^q) = \frac{1}{(2\pi)^{N/2}\sqrt{\det \mathbf{C}}} \exp[-(\mathbf{Y}^q - \mu)^H \mathbf{C}^{-1} (\mathbf{Y}^q - \mu) / 2] \tag{3.15}$$

with mean vector μ and covariance matrix **C**.

The PDF thus becomes

$$f(\mathbf{Y}^q / \mathbf{A}, \mathbf{h}^q) = \frac{1}{(2\pi)^{N/2}\sigma_w^N} \exp[-(\frac{1}{2\sigma_w^2})(\mathbf{Y}^q - \mathbf{A}\mathbf{h}^q)^H (\mathbf{Y}^q - \mathbf{A}\mathbf{h}^q)] \tag{3.16}$$

whereas the PDF of A is determined from a-priori probabilities of transmitted symbols. The maximization step involves differentiating L in (3.14) with respect to $\mathbf{h}^q$ and finding the channel parameter which maximizes the log-likelihood. Thus we have,

$$\frac{\partial}{\partial \mathbf{h}^q}\left[\sum_{\mathbf{X}\in X} \frac{\log(f(\mathbf{Y}^q / \mathbf{A}_\mathbf{X}, \mathbf{h}^q) f(\mathbf{A}_\mathbf{X}))}{f(\mathbf{Y}^q / \mathbf{A}_\mathbf{X}, \mathbf{h}_i^q) f(\mathbf{A}_\mathbf{X})}\right] = 0$$

$$\text{i.e.}\ \hat{\mathbf{h}}^{q^H} = \left[\sum_{\mathbf{X}\in X} \mathbf{Y}^{q^H} \mathbf{A}_\mathbf{X} f(\mathbf{Y}^q / \mathbf{A}_\mathbf{X}, \mathbf{h}_i^q)\right] \left[\sum_{\mathbf{X}\in X} \mathbf{A}_\mathbf{X}^H \mathbf{A}_\mathbf{X} f(\mathbf{Y}^q / \mathbf{A}_\mathbf{X}, \mathbf{h}_i^q)\right]^{-1} \tag{3.17}$$

If the conventional EM algorithm is used directly for channel estimation using (3.17), then computational complexity increases. In [26], hard VBLAST EM algorithm is considered for semi-blind channel estimation in MIMO-OFDM.

3.3.2. Semi-blind channel estimation for MIMO-OFDM using hard VBLAST-EM algorithm

In hard VBLAST-EM channel estimation technique, plain VBLAST algorithm is used for data detection. VBLAST algorithm involves removing the effect of already detected symbols (assuming those decisions to be correct) and linearly combining the received symbols, in such a way that it reduces the interference from yet-to-be-detected symbols. The hard VBLAST-EM technique involves applying the PACE based channel $\hat{\mathbf{h}}^q$ as input to plain VBLAST algorithm and then applying the VBLAST algorithm on each subcarrier of the OFDM symbols received on N_r antennas. The relation between transmitted and received symbols in an alternative form can be written as follows

$$\mathbf{y}(k) = \mathbf{H}(k)\mathbf{x}(k) + \mathbf{n}(k), \tag{3.18}$$

where $\mathbf{y}(k)$ is the $N_r \times 1$ vector of signal values received on subcarrier k , $\mathbf{x}(k)$ is the $N_t \times 1$ vector of symbols transmitted from the N_t antennas on subcarrier k, and H(k) is the $N_r \times N_t$ matrix of channel frequency response values, whose (p,q)th element is given by $H^{(q,p)}(k)$.

The plain VBLAST detection algorithm [25] for MIMO-OFDM system is a simple approach capable of achieving efficient detection at high spectral efficiencies. Here, VBLAST algorithm with optimal ordering and nulling is used.

The first step of hard VBLAST-EM algorithm involves applying available estimates $\hat{\mathbf{h}}^{q,p}$ of channel tap vector $\mathbf{h}^{q,p}$ from PACE. Channel tap vector $\mathbf{h}^{q,p}$ are transferred to frequency domain to obtain the channel frequency response matrix $\hat{H}(k)$ for $0 \le k \le N-1$.

In next step, hard VBLAST algorithm gives the estimates of transmitted data symbols from each antenna over each OFDM carrier. Then, we take the expectation over these transmit data estimates and log-likelihood function in (3.14) becomes

$$L = \log(f(\mathbf{Y}^q / \mathbf{A}_{\hat{\mathbf{X}}}, \mathbf{h}_i^q) f(\mathbf{A}_{\hat{\mathbf{X}}}) \tag{3.19}$$

maximization of this function leads to

$$\frac{\partial}{\partial \mathbf{h}^q}(L) = \frac{\partial}{\partial \mathbf{h}^q}\begin{bmatrix} \log\left(\dfrac{1}{(2\pi)^{N/2}\sigma_w^N} f(\mathbf{A}_{\hat{\mathbf{X}}})\right) \\ -(\dfrac{1}{2\sigma_w^2})(\mathbf{Y}^q - \mathbf{A}_{\hat{\mathbf{X}}}\mathbf{h}^q)^H(\mathbf{Y}^q - \mathbf{A}_{\hat{\mathbf{X}}}\mathbf{h}^q) \end{bmatrix} . \tag{3.20}$$

This reduces to

$$\frac{\partial}{\partial \mathbf{h}^q}\left[\mathbf{h}^{q^H}\mathbf{A}_{\hat{\mathbf{X}}}^H\mathbf{A}_{\hat{\mathbf{X}}}\mathbf{h}^q - \mathbf{Y}^{q^H}\mathbf{A}_{\hat{\mathbf{X}}}\mathbf{h}^q\right] = 0 \tag{3.21}$$

and hence

$$\hat{\mathbf{h}}^q = \left[(\mathbf{Y}^{q^H}\mathbf{A}_{\hat{\mathbf{X}}})(\mathbf{A}_{\hat{\mathbf{X}}}^H\mathbf{A}_{\hat{\mathbf{X}}})^{-1}\right]^H \tag{3.22}$$

This is evidently simpler to compute than (3.17).

The algorithm may be summarized as follows:

1) Using P pilot tones in the first OFDM symbol of the frame, the receiver obtains rough channel estimates using PACE as in (3.10).

2) The estimates obtained from PACE are used to run hard VBLAST algorithm and estimates of transmitted data $\hat{\mathbf{X}}$ are found.

3) Corresponding to the estimates, matrix $\mathbf{A}_{\hat{\mathbf{X}}}$ is computed and used in (3.22) to improve channel estimates.

4) Steps 2) and 3) are iterated until convergence.

3.4. Simulation results

The hard VBLAST-EM channel estimation technique is tested through Monte Carlo simulations. We consider a MIMO-OFDM with two transmit antennas (N_t=2) and two receive antennas (N_r) with 128 subcarrier OFDM system. A Rayleigh multipath fading channel model with time varying environment are considered. Fading channel is modeled with L=2 taps and the SUI-MIMO channel with correlation coefficients ρ_t=0.2 and ρ_r=0.4 are used. The convolutional code with a rate ½ code, constraint length of 7 and generator polynomials specified by {712} and {476} in octal notation is used. We use QPSK as the underlying modulation scheme. The channel is assumed to be quasi static and does not vary with in each frame and channel varies for each frame according to Doppler values. . Each frame consists of 30 symbols. We have taken Doppler values of f_dT=0.005and f_dT=0.05 respectively [27]. Simulation has been done in MATLAB environment. The system performance is evaluated for SNR values of 0-20db by averaging over 500 frames.

The performance curves using hard VBLAST-EM based channel estimation technique is shown below.We generate 100 independent realizations of the channel at each value of SNR for averaging. PACE is carried out by using 16 pilots. The estimates from PACE are used to initialize the hard VBLAST-EM based channel estimation technique. The BER performance obtained when exact channel state information(CSI) is known is also plotted for comparison.

Figure 3.3 and figure 3.4 respectively shows mean square estimation error (MSEE) performance for Doppler value of f_dT=0.005 and f_dT=0.05. MSEE of PACE and hard VBLAST-EM is obtained through (3.23).

$$MSEE = \frac{1}{RN_r N_t L} \sum_{r=1}^{R} \sum_{q=1}^{N_r} \left\| \mathbf{h}^q - \hat{\mathbf{h}}^q \right\|^2 \tag{3.23}$$

where R is the number of independent channel realizations used for averaging, $\mathbf{h}^q$ and $\hat{\mathbf{h}}^q$ respectively denotes the actual and estimated channel vector. PACE achieves a MSEE of 0.0044 where as hard VBLAST-EM achieves the MSEE of 0.0020 at SNR of 19dB for $f_d T$=0.005. The performance of hard VBLAST-EM improves by 2-3dB as compared to PACE curve at high SNRs. PACE achieves a MSEE of 0.0265 where as hard VBLAST-EM achieves the MSEE of 0.0160 at SNR of 19dB for $f_d T$=0.05. The performance of hard VBLAST-EM improves by 1-2dB as compared to PACE curve at high SNRs.

Figure 3.5 shows BER performance for Doppler value of $f_d T$=0.005.BER performance curve for PACE using 16 pilots achieves a BER of 0.0038 at SNR of 19dB. BER performance cuvre for hard VBLAST-EM achieves a BER of 0.0015 at SNR of 19dB. The performance lies within 8-9dB of exact CSI curve at high SNRs. Figure 3.6 shows BER performance for Doppler value of $f_d T$=0.05. BER performance curve for PACE using 16 pilots achieves a BER of 0.1085 at SNR of 19dB. BER performance cuvre for hard VBLAST-EM achieves a BER of 0.0083 at SNR of 19dB. The performance of hard VBLAST-EM improves at the Doppler value of $f_d T$=0.005 as compared to the Doppler value of $f_d T$=0.05.

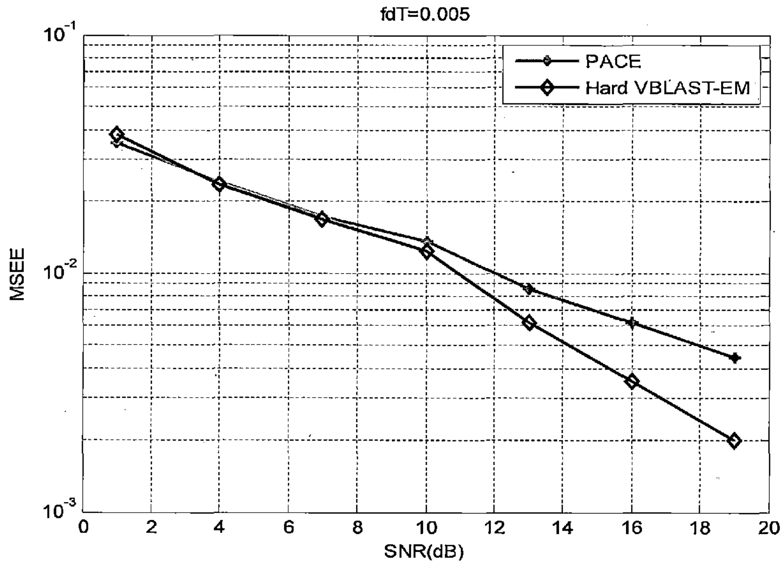


Figure 3.3. Comparison of MSEE performance for hard VBLAST-EM and pilot based channel estimation techniques in time varying fading environment for MIMO-OFDM systems(f_dT=0.005).

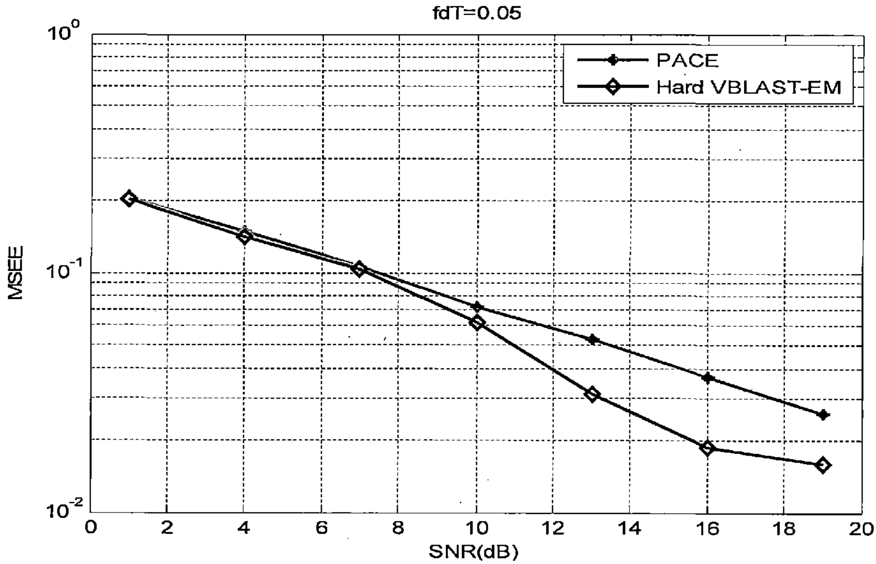


Figure 3.4. Comparison of MSEE performance for hard VBLAST-EM and pilot based channel estimation techniques in time varying fading environment for MIMO-OFDM systems($f_d T$=0.05).

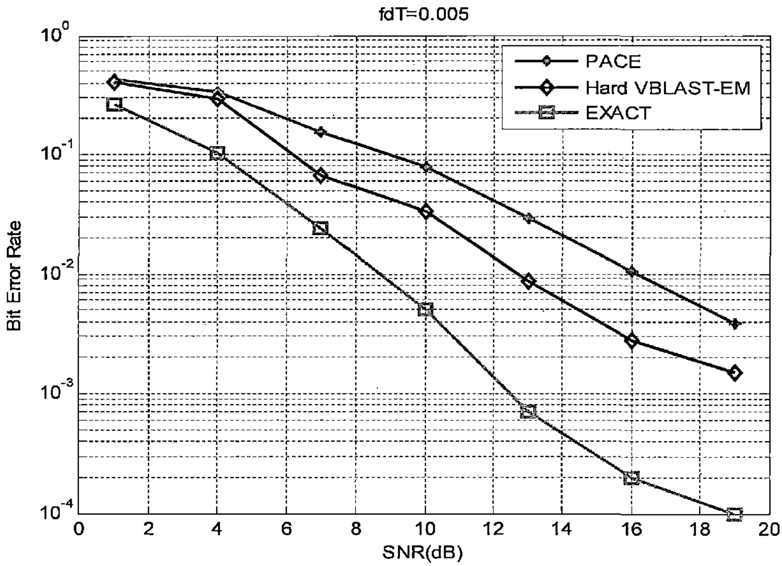


Figure 3.5. Comparison of BER performance for hard VBLAST-EM and pilot based channel estimation techniques in time varying fading environment for MIMO-OFDM systems(f_dT=0.005).

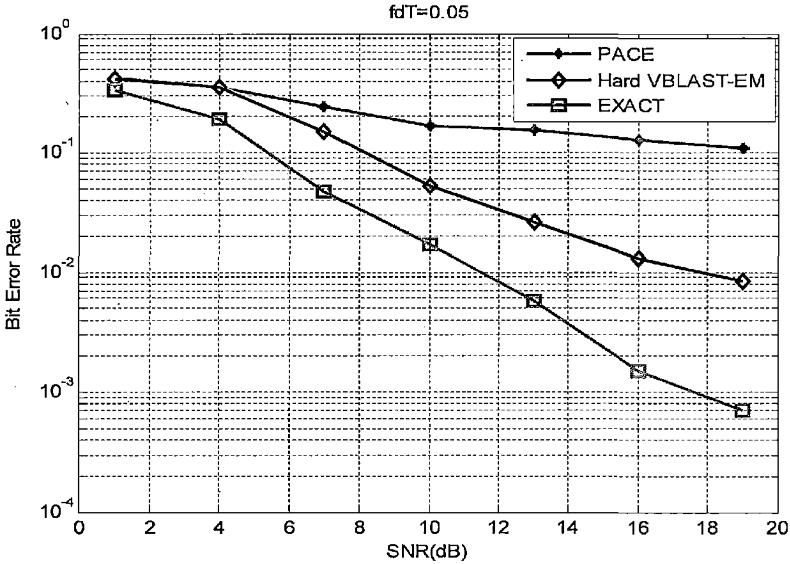


Figure 3.6. Comparison of BER performance for hard VBLAST-EM and pilot based channel estimation techniques in time varying fading environment for MIMO-OFDM systems(f_dT=0.05).

Chapter 4
Iterative Detection and Decoding for MIMO-OFDM using soft VBLAST-EM algorithm

In this chapter, soft VBLAST-EM based channel estimation for MIMO-OFDM systems is presented first. Next, an iterative detection and decoding (IDD) scheme is discussed. Simulation results on the performance of soft VBLAST-EM based channel estimation for MIMO-OFDM systems with IDD scheme are presented at the end.

4.1. Soft VBLAST-EM based channel estimation for MIMO-OFDM systems

The first step of this technique involves applying soft VBLAST [28] algorithm on each subcarrier of the OFDM symbol received on each of the N_r antennas. Soft VBLAST algorithm is an improved VBLAST, which takes the error propagation effect into account. Define the transmitted symbols as a signal vector $\mathbf{x}_k = \left[x_k^1\ x_k^2 \cdots x_k^{N_t}\right]^T$, where x_k^n represents the symbol transmitted from the n$^{\text{th}}$ antenna at the k$^{\text{th}}$ sub channel and $\hat{x}_k^n$ is the detected symbol for layer n. The ordering of the decisions is made according to the optimal detection order assumed to be available. In the conventional V-BLAST algorithm, the predetected symbol vector $\hat{\mathbf{x}}_k^{i-1}$ until step i-1 is cancelled out from the received vector signal at step i, resulting in the modified received vector $\mathbf{y}_k^i$ given by

$$\mathbf{y}_k^i = \mathbf{y} - \mathbf{H}_k^{1:i-1}\hat{\mathbf{x}}_k^{i-1} = \mathbf{H}_k^{i:N_t}\mathbf{x}_k^i + \mathbf{n}_k, \qquad (4.1)$$

assuming all previous decisions are correct $(\hat{x}_k^n = x_k^n \ for\, n = 1,2,\ldots i-1)$. At step i, in order to detect x_k^i, the remaining undetected symbols $[x_k^i,\ldots x_k^{i-1}, x_k^{i+1},\ldots, x_k^{N_t}]$ are treated as interferers. But in the presence of decision errors (4.1) becomes

$$\mathbf{y}_k^i = \mathbf{H}_k^{i:N_t}\mathbf{x}_k^i + \mathbf{H}_k^{i:i-1}\hat{\mathbf{e}}_k^{i-1} + \mathbf{n}_k \qquad (4.2)$$

where $\hat{\mathbf{e}}_k^{i-1} = \left[e_k^1,\ldots,e_k^{i-1}\right]^T$ is defined with $\mathbf{e}_k^n = x_k^n - \hat{x}_k^n$.

The equalizer matrix for nulling the effects of already detected symbols is determined using MMSE criterion and this matrix also accounts for the decision errors and is defined as

$$\mathbf{G} = \mathbf{H}_k^{i:N_t\dagger}\left(\mathbf{H}_k^{i:N_t}\mathbf{H}_k^{i:N_t\dagger} + \frac{1}{\sigma_s^2}\mathbf{H}_k^{1:i-1}\mathbf{Q}_{\tilde{\mathbf{e}}_k^{i-1}}\mathbf{H}_k^{1:i-1\dagger} + \alpha\mathbf{I}_{N_r}\right)^{-1} \tag{4.3}$$

where $i \in \{1,2,\ldots,N_t\}$ denotes the current symbol being detected according to the optimal order, $\mathbf{H}_k^{i:N_t}$ is the matrix having $N_t - i + 1$ columns from H_k corresponding to undetected symbols, $\mathbf{Q}_{\tilde{\mathbf{e}}_k^{i-1}}$ is the $(i-1)\times(i-1)$ error covariance matrix for decisions already made, $\mathbf{H}_k^{1:i-1}$ forms the $(i-1)$ columns of H_k relating to already detected symbols and $\alpha = \sigma_n^2 / \sigma_s^2$. The $\mathbf{Q}_{\tilde{\mathbf{e}}_k^{i-1}}$ matrix is given by

$$\mathbf{Q}_{\tilde{\mathbf{e}}_k^{i-1}} = \begin{bmatrix} E\left[\left|e_k^1\right|^2 \left|\hat{x}_k^1\right.\right] & \cdots & E\left[e_k^1 e_k^{i-1*}\left|\hat{x}_k^1, \hat{x}_k^{i-1}\right.\right] \\ \vdots & \ddots & \\ E\left[e_k^{i-1} e_k^{1*}\left|\hat{x}_k^{i-1}, \hat{x}_k^1\right.\right] & \cdots & E\left[\left|e_k^{i-1}\right|^2\left|\hat{x}_k^{i-1}\right.\right] \end{bmatrix}$$

The approximation of $\mathbf{Q}_{\tilde{\mathbf{e}}_k^{i-1}}$ with reduced complexity leads to

$$\mathbf{Q}_{\tilde{\mathbf{e}}_k^{i-1}} = diag\left[E\left[\left|e_k^1\right|^2\left|\hat{x}_k^1\right.\right], \ldots, E\left[\left|e_k^{i-1}\right|^2\left|\hat{x}_k^{i-1}\right.\right]\right] \tag{4.4}$$

Diagonal elements of $\mathbf{Q}_\mathbf{e}$ then represent the MSE value for each of the detected symbol. $\tilde{x}_k^t$ can be computed as $\tilde{x}_k^t = \beta x_k^t + w$ (4.5)

where $\beta = \mathbf{g}_t \mathbf{h}_k^t$ and $w = \sum_{j=1}^{N} \mathbf{g}_t \mathbf{h}_k^j x_k^j + \mathbf{g}_t \mathbf{H}_k^{1:i-1} \hat{\mathbf{e}}_k^{i-1} + \mathbf{g}_t \mathbf{n}_k$

$\mathbf{g}_t$ is the t^th^ row of G. For next step i+1, the conditional expected value $E\left[\left|e_k^t\right|^2\left|\hat{x}_k^t\right.\right]$ can be obtained as

$$E\left[\left|e_k^t\right|^2\left|\hat{x}_k^t\right.\right] = \sum_{s\in N_{\hat{x}_k^t}} \left|s - \hat{x}_k^t\right|^2 \mathbf{P}\left(x_k^t = s\left|\tilde{x}_k^t\right.\right) \tag{4.6}$$

where $N_{\hat{x}_k^t}$ consists of the neighboring constellation points surrounding the hard decision point $\hat{x}_k^t$. The conditional probability $\mathbf{P}\left(x_k^t = s \middle| \hat{x}_k^t\right)$ can be computed as

$$\mathbf{P}\left(x_k^t = s \middle| \hat{x}_k^t\right) = \begin{cases} 1 - 2P_e + P_e^2, & \text{if } s = \hat{x}_t \\ P_e - P_e^2, & \text{if } s \text{ is one of two nearest neighbors of } \hat{x}_t \\ P_e^2, & \text{else} \end{cases}$$

where P_e is the probability of error for QPSK and is given by $P_e = Q\left(\sqrt{\frac{\beta}{1-\beta}}\right)$. After computing (4.6), this term is added to the covariance matrix $\mathbf{Q}_{\tilde{e}_k^i}$ for next step i+1. The conditional pdf of $\tilde{x}_k^t$ is given by

$$p\left(\tilde{x}_k^t \middle| x_k^t = s\right) = \frac{1}{\pi\sigma_w^2}\exp\left(-\frac{\left|\tilde{x}_k^t - \beta s\right|^2}{\sigma_w^2}\right) \tag{4.7}$$

Let S be a set of constellation symbols and s denotes an element of the S. The aposteriori LLR of $b_k^{t,i}$ can be defined as

$$L\left(b_k^{t,i}\right) = \log \frac{\sum_{s \in S_0^i} \exp\left(-\frac{\left|\tilde{x}_k^t - \beta s\right|^2}{\sigma_w^2}\right)}{\sum_{s \in S_1^i} \exp\left(-\frac{\left|\tilde{x}_k^t - \beta s\right|^2}{\sigma_w^2}\right)} \tag{4.8}$$

S_1^i and S_0^i denotes the set of constellation points in which the i$^{\text{th}}$ bit is 0 or 1, respectively. These LLRs are used to find the probability of each bit being 0 or 1 as follows

$$P\left[b_k^{t,i} = b\right] = \begin{cases} \dfrac{\exp\left(L\left(b_k^{t,i}\right)\right)}{1 + \exp\left(L\left(b_k^{t,i}\right)\right)}, & b = 0 \\ \dfrac{1}{1 + \exp\left(L\left(b_k^{t,i}\right)\right)}, & b = 1 \end{cases} \tag{4.9}$$

with these, the estimate of the transmitted symbol is computed as

$$\hat{\mathbf{x}}_k^t \doteq \sum_{s \in S} s\, P\left(x_k^i = s\right) \tag{4.10}$$

where S is the constellation being used.

The algorithm may thus be summarized as follows [26]

1) Using P pilot tones in the first OFDM symbol of the frame, the receiver obtains rough channel estimates using PACE as in (3.10).
2) The estimates obtained from PACE are used to run soft VBLAST algorithm and LLR values (4.8) are used to find the estimates of transmitted data $\hat{\mathbf{x}}$ from (4.9) and (4.10).
3) Corresponding to the estimates, matrix $\mathbf{A}_{\hat{\mathbf{x}}}$ is computed and used in (3.22) to improve channel estimates.
4) Steps 2) and 3) are iterated until convergence.

4.1.1. Iterative Detection and Decoding [28]:

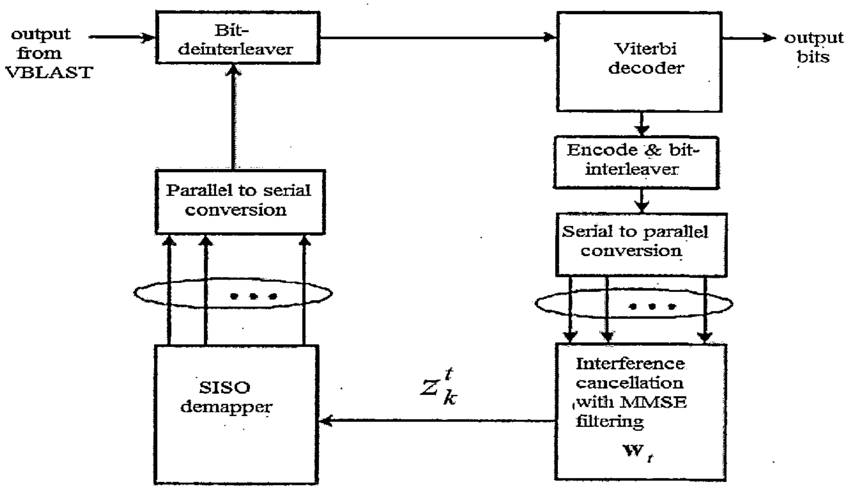


Figure 4.1. Iterative Detection and Decoding (IDD)

The channel coding gain is exploited to further improve the performance by using IDD. In this, SISO (single-input single-output) demapper is used which simplifies the computational complexity. In SISO demapper, the number of values require to compute the LLRs are only M (M is constellation size) for any antenna configuration. The structure of IDD scheme is shown in figure 4.1. The estimates of transmitted symbols over different subcarriers of multiple antennas are available to the IDD block from soft VBLAST-EM technique. The P/S and de-interleaving operations are carried out to the estimated transmitted symbols. The de-interleaved bit estimates are decoded with a Viterbi decoder and resulting bit stream is used to regenerate the estimate of transmitted symbols. Let $\hat{\mathbf{x}}_k$ be the estimate of $N_t \times 1$ vector of transmitted symbols. The optimal order determined by soft VBLAST technique at each carrier is assumed to be available and this information can be used in the interference cancellation. Let t denote the location in the set $\{1,2,\ldots,N_t\}$ corresponding to the current symbol being detected. In order to detect x_k^t, the hard decisions for all the other symbols $x_k^1,\ldots,x_k^t,x_k^{t+1},\ldots,x_k^{N_t}$ are used to cancel the interference from $\mathbf{y}_k$.For interference cancellation at t, we form a vector as

$$\hat{\underline{\mathbf{x}}}_k^t = \left[\hat{x}_k^1,\ldots,\hat{x}_k^{t-1},0,\hat{x}_k^{t+1},\ldots,\hat{x}_k^{N_t} \right]$$

The received signal $\mathbf{y}_k$ is modified by cancelling the interference $\hat{\underline{\mathbf{x}}}_k^t$ as

$$\underline{\mathbf{y}}_k^t = \mathbf{y}_k - \mathbf{H}_k \hat{\underline{\mathbf{x}}}_k^t \quad for\ k = 1,2,\ldots,N \tag{4.11}$$

Where $\mathbf{H}_k$ is the estimate of channel frequency response vector available from soft VBLAST-EM technique, $\underline{\mathbf{x}}_k^t = \left[e_k^1,\ldots e_k^{t-1}, x_k^t, e_k^{t+1},\ldots,e_k^{N_t} \right]$ and $e_k^i = x_k^i - \hat{x}_k^i$. In order to get transmitted symbol x_k^t, MMSE filter $\mathbf{w}_t$ is applied to the modified received vector. The MMSE filter vector $\mathbf{w}_t$, which is a $1 \times N_r$ vector, minimizes the variance of the estimation error defined as $e = x_k^t - \mathbf{w}_t \underline{\mathbf{y}}_k^t$,

when Viterbi decoder is used, the filter weight are found to be [29]

$$\mathbf{w}_t = \mathbf{h}_k^t / \left(\left| \mathbf{h}_k^t \right|^2 + \sigma_n^2 / \sigma_s^2 \right) \tag{4.12}$$

Applying this filter to the received symbol vector $\underline{\mathbf{y}}_k^t$ gives

$$z_k^t = \mathbf{w}_t \underline{\mathbf{y}}_k^t$$

$$= \alpha x_k^t + v \tag{4.13}$$

which is a biased estimate of the transmitted symbol x_k^t, for $1 \le t \le N_t$ and $0 \le k \le N-1$. Let $d_k^{t,m}$ be the m$^{\text{th}}$ bit ($1 \le m \le \log_2 M$) of the constellation symbol at the t$^{\text{th}}$ transmit antenna $(t = 1,2,\ldots,N_t)$ at the k$^{\text{th}}$ subcarrier, the constellation has M complex data points. $L(d_k^{t,m})$ is the log likelihood ratio (LLR) vale for the bit $d_k^{t,m}$. The LLR values $d_k^{t,m}$ are given by

$$L(d_k^{t,m}) = \log \frac{\sum_{s \in S_0^m} \exp\left(-\frac{\left|\tilde{z}_k^t - \alpha s\right|^2}{\sigma_v^2}\right)}{\sum_{s \in S_1^m} \exp\left(-\frac{\left|\tilde{z}_k^t - \alpha s\right|^2}{\sigma_v^2}\right)} \tag{4.14}$$

Here $\alpha = \mathbf{w}_t \mathbf{h}_k^t$ and $\sigma_v^2 = \sigma_s^2 (\alpha - \alpha^2)$,

S_0^m and S_1^m denote the set of constellation points in which the m$^{\text{th}}$ bit is 0 or 1, respectively.

These LLRs are used to find the probability of each bit being 0 or 1 as follows

$$P\left[b_k^{t,m} = b\right] = \begin{cases} \dfrac{\exp\left(L\left(b_k^{t,m}\right)\right)}{1+\exp\left(L\left(b_k^{t,m}\right)\right)}, & b = 0 \\ \dfrac{1}{1+\exp\left(L\left(b_k^{t,m}\right)\right)}, & b = 1 \end{cases} \tag{4.15}$$

with these, the estimate of the transmitted symbol computed as

$$\hat{\mathbf{x}}_k^t = \sum_{s \in \mathbf{S}} s\, P\left(x_k^m = s\right) \tag{4.16}$$

where S is the constellation being used.

The iterative procedure of IDD scheme is summarized as follows

1. The estimates of channel frequency response and transmitted symbols are given as input to IDD block.
2. Bit-deinterleaving and Viterbi decoding operations are carried out on the estimates of transmitted symbols, to get the bit stream.
3. The bit stream is encoded, bit-interleaved and then converted into symbols using S/P converter. The output of S/P converter is given as input to MMSE filter.
4. The MMSE filter gives the biased estimate of the transmitted symbol x_k^l as in (4.12) & (4.13).
5. LLR values are next obtained from (4.14) and are used to find the estimates of transmitted symbols using (4.15) and (4.16). This constitutes SISO demapper.
6. The estimates of transmitted symbols are P/S converted.
7. Steps (1) to (6) are iterated to improve the performance.

Scheme for Iterative Detection and Decoding using soft VBLAST-EM based channel estimation for MIMO-OFDM system is shown in figure 4.2.

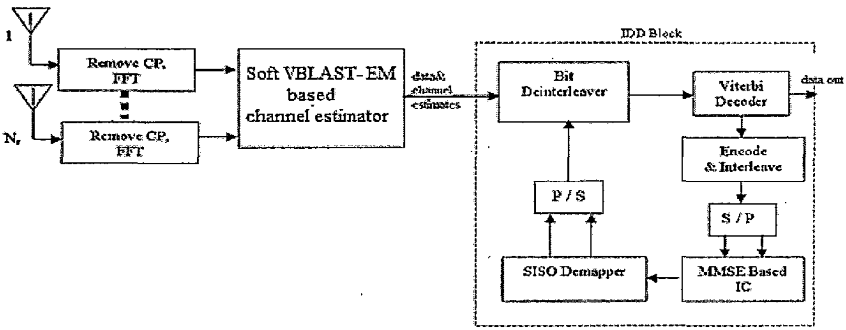


Figure 4.2. Scheme for Iterative Detection and Decoding using soft VBLAST-EM based channel estimation for MIMO-OFDM system

4.2. Simulation results

The soft VBLAST-EM channel estimation technique when the system is coupled with IDD block is tested through Monte Carlo simulations. We consider a MIMO-OFDM with two transmit antennas (N_t=2) and two receive antennas (N_r=2) with 128 subcarrier OFDM system. A Rayleigh multipath fading channel model with time varying environment is considered. Fading channel is modeled with L=2 taps and the SUI-MIMO channel with correlation coefficients ρ_t=0.2 and ρ_r=0.4 are used [26]. The convolutional code with a rate ½ code, constraint length of 7 and generator polynomials specified by {712} and {476} in octal notation is used. We use QPSK as the underlying modulation scheme. The channel is assumed to be quasi static and does not vary with in each frame and channel varies for each frame according to Doppler values. We have taken Doppler values of f_dT =0.005and f_dT=0.05 respectively. Each frame consists of 30 symbols. Simulation has been done in MATLAB environment. The system performance is evaluated for SNR values of 0-20db by averaging over 500 frames.

The performance curves using soft VBLAST-EM based channel estimation technique is shown below.We generate 50 independent realizations of the channel at each value of SNR for averaging. PACE is carried out by using 16 pilots. The estimates from PACE are used to initialize the soft VBLAST-EM based channel estimation technique. The BER performance obtained when exact channel state information(CSI) is known is also plotted for comparison.

Figure 4.3 & figure 4.4 respectively shows mean square estimation error(MSEE) performance for Doppler value of f_dT=0.005 and f_dT=0.05. MSEE of PACE and soft VBLAST-EM is obtained through (4.17).

$$MSEE = \frac{1}{RN_rN_tL}\sum_{r=1}^{R}\sum_{q=1}^{N_r}\left\|\mathbf{h}^q - \hat{\mathbf{h}}^q\right\|^2 \qquad (4.17)$$

Where R is the number of independent channel realizations used for averaging, $\mathbf{h}^q$ and $\hat{\mathbf{h}}^q$ respectively denotes the actual and estimated channel vector. PACE achieves a MSEE of 0.0044 where as soft VBLAST-EM achieves the MSEE of 0.0016 at SNR of 19dB for f_dT=0.005. The performance of soft VBLAST-EM improves by 2-3dB as compared to PACE curve at high SNRs. PACE achieves a MSEE of 0.0257 where as soft VBLAST-EM achieves the MSEE of 0.0088 at SNR of 19dB for $f_d T$=0.05. The MSEE performance for doppler value of $f_d T$=0.005 gives better performance as compared to $f_d T$=0.05. The performance of soft VBLAST-EM improves to 2-3dB as compared to PACE curve at high SNRs.

Figure 4.5 shows BER performance of the system using soft VBLAST-EM, when coupled with IDD block for Doppler value of $f_d T$=0.005. It may be seen that as the number of iterations increases, the BER performance improves. BER performance curve for soft VBLAST-EM for one iteration of the IDD structure achieves a BER of 0.0048 at SNR of 19dB. As the iterations of IDD structure increases to four, the BER performance improves and acheives the BER of 0.0004 at SNR of 19dB. The BER performance improves to within 3-4 dB of exact CSI curve at high SNRs as iterations of IDD block increases to 4.

Figure 4.6 shows BER performance of the system using PACE, when coupled with IDD block for Doppler value of $f_d T$=0.005. BER performance curve for PACE using 16 pilots for one iteration of the IDD structure achieves a BER of 0.0071 at SNR of 19dB. As the iterations of IDD structure increases to four, the BER performance improves and acheives the BER of 0.0008 at SNR of 19dB.

Figure 4.7 shows BER performance of the system using soft VBLAST-EM, when coupled with IDD block for Doppler value of $f_d T$=0.05. It may be seen that as the number of iterations increases, the BER performance increases. BER performance curve for soft VBLAST-EM for one iteration of the IDD structure achieves a BER of 0.0724 at SNR of 19dB. As the iterations of IDD structure increases to four, the BER performance improves and acheives the BER of 0.0053 at SNR of 19dB. The BER performance improves to within 6-7 dB of exact CSI curve at high SNRs.

Figure 4.8 shows BER performance of the system using PACE, when coupled with IDD block for Doppler value of $f_d T$=0.05. BER performance curve for PACE using 16 pilots for one iteration of the IDD structure achieves a BER of 0.0909 at SNR of 19dB. As the number iterations of IDD structure increases to four, the BER performance improves and acheives the BER of 0.0247 at SNR of 19dB.

Figure 4.8 shows BER performance of the system using PACE, when coupled with IDD block for Doppler value of f_dT=0.05. BER performance curve for PACE using 16 pilots for one iteration of the IDD structure achieves a BER of 0.0909 at SNR of 19dB. As the number iterations of IDD structure increases to four, the BER performance improves and acheives the BER of 0.0247 at SNR of 19dB.

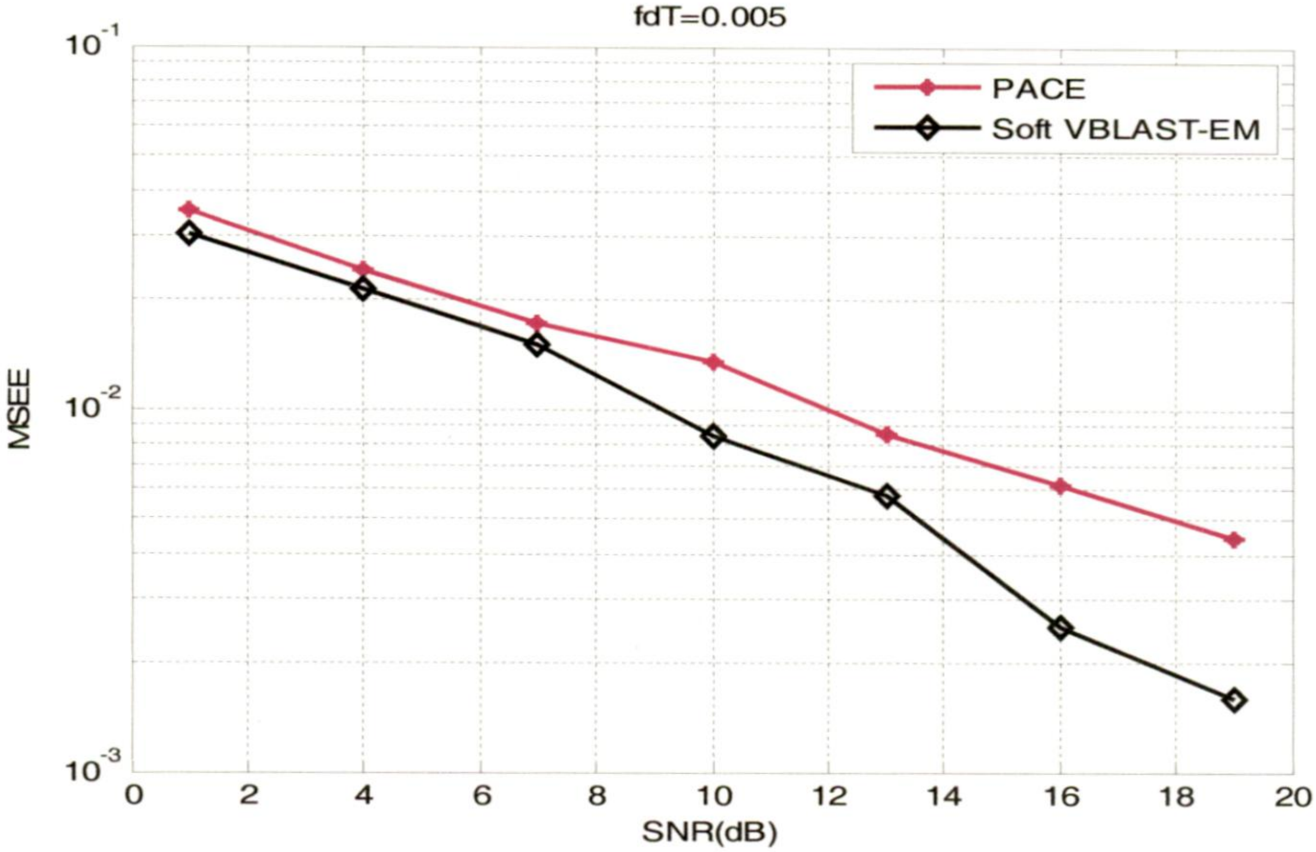


Figure 4.3. Comparison of MSEE performance for soft VBLAST-EM and pilot based channel estimation techniques in time varying fading environment for MIMO-OFDM systems(f_dT=0.005).

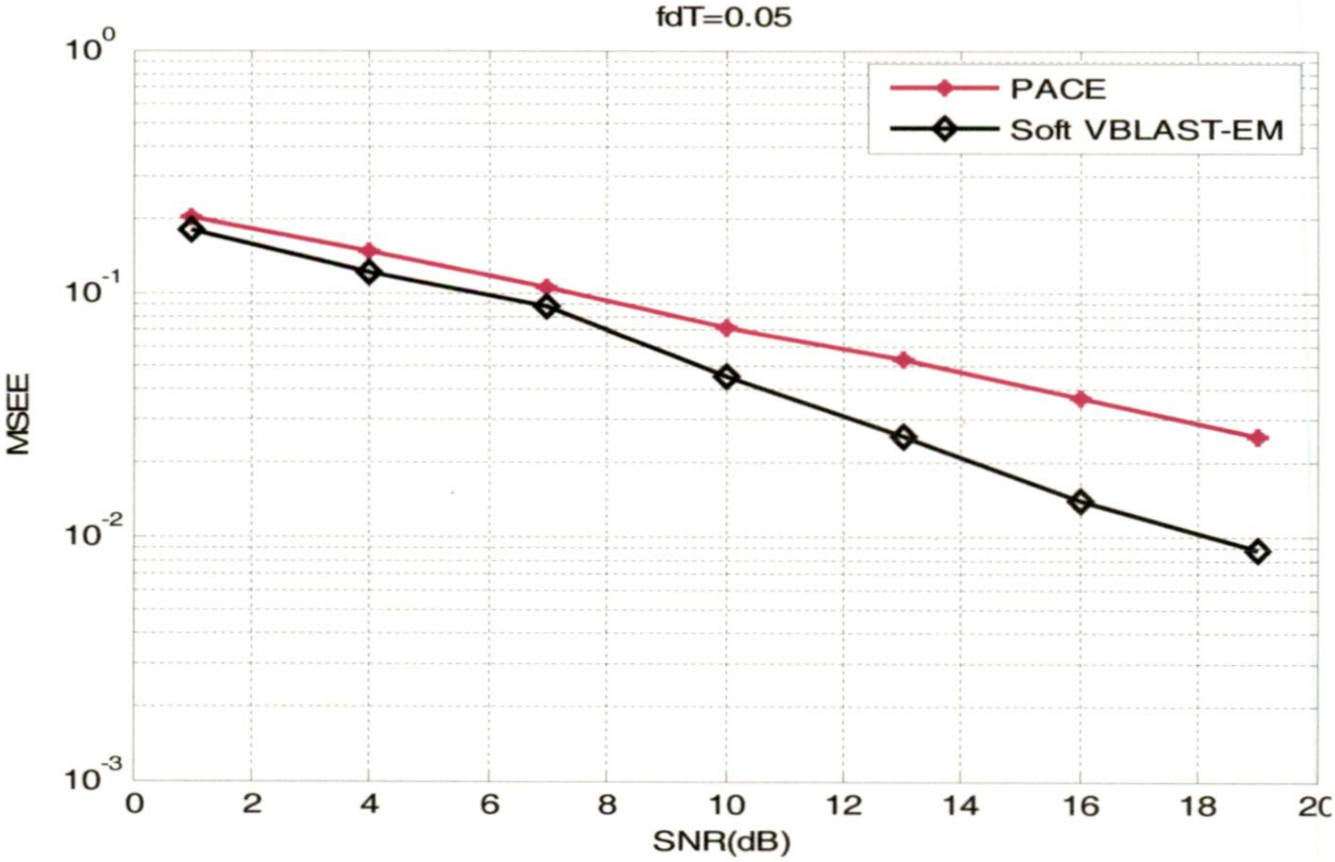


Figure 4.4. Comparison of MSEE performance for soft VBLAST-EM and pilot based channel estimation techniques in time varying fading environment for MIMO-OFDM systems($f_d T$ =0.05).

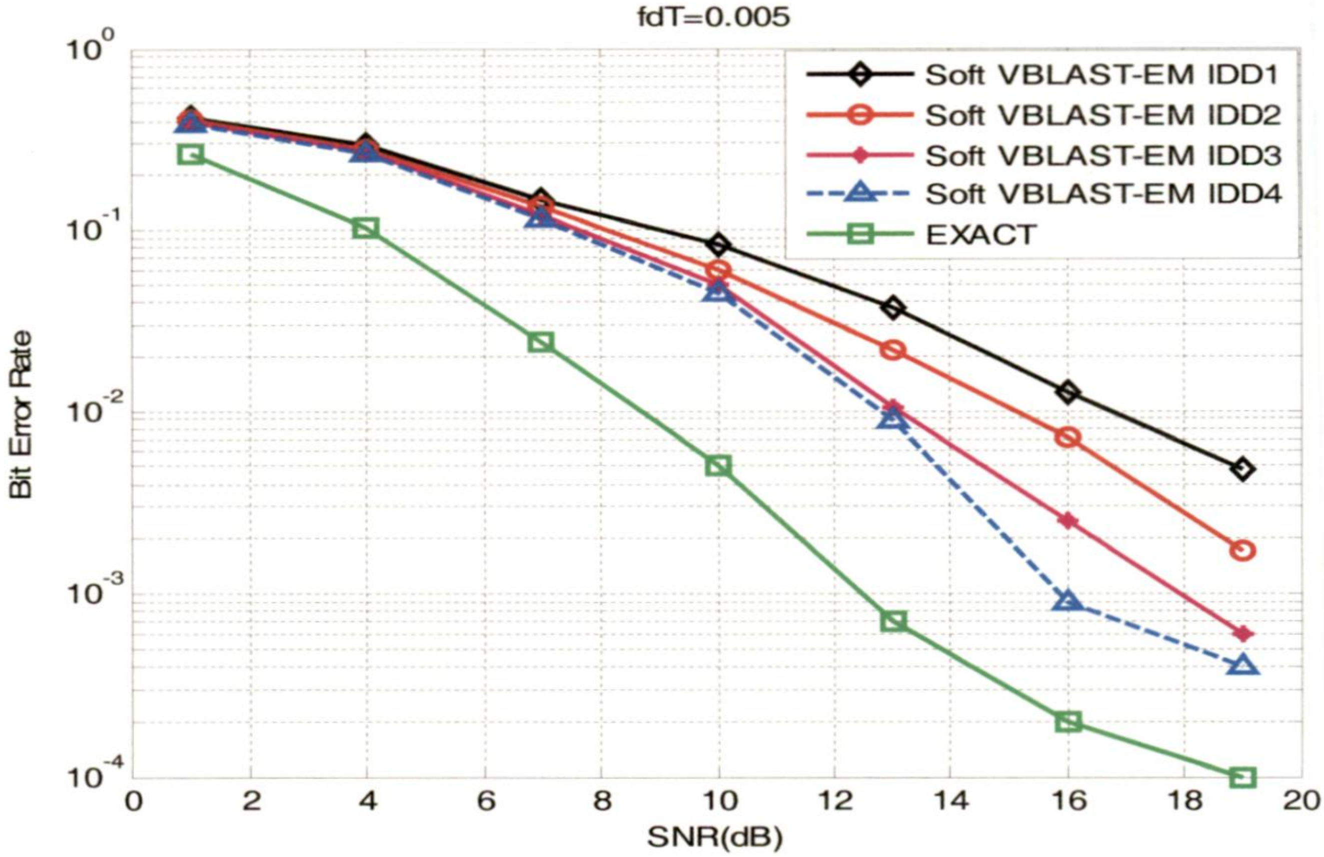


Figure 4.5. Comparison of BER performance for soft VBLAST-EM based channel estimation technique with different IDD iterations in time varying fading environment for MIMO-OFDM systems($f_d T$ =0.005).

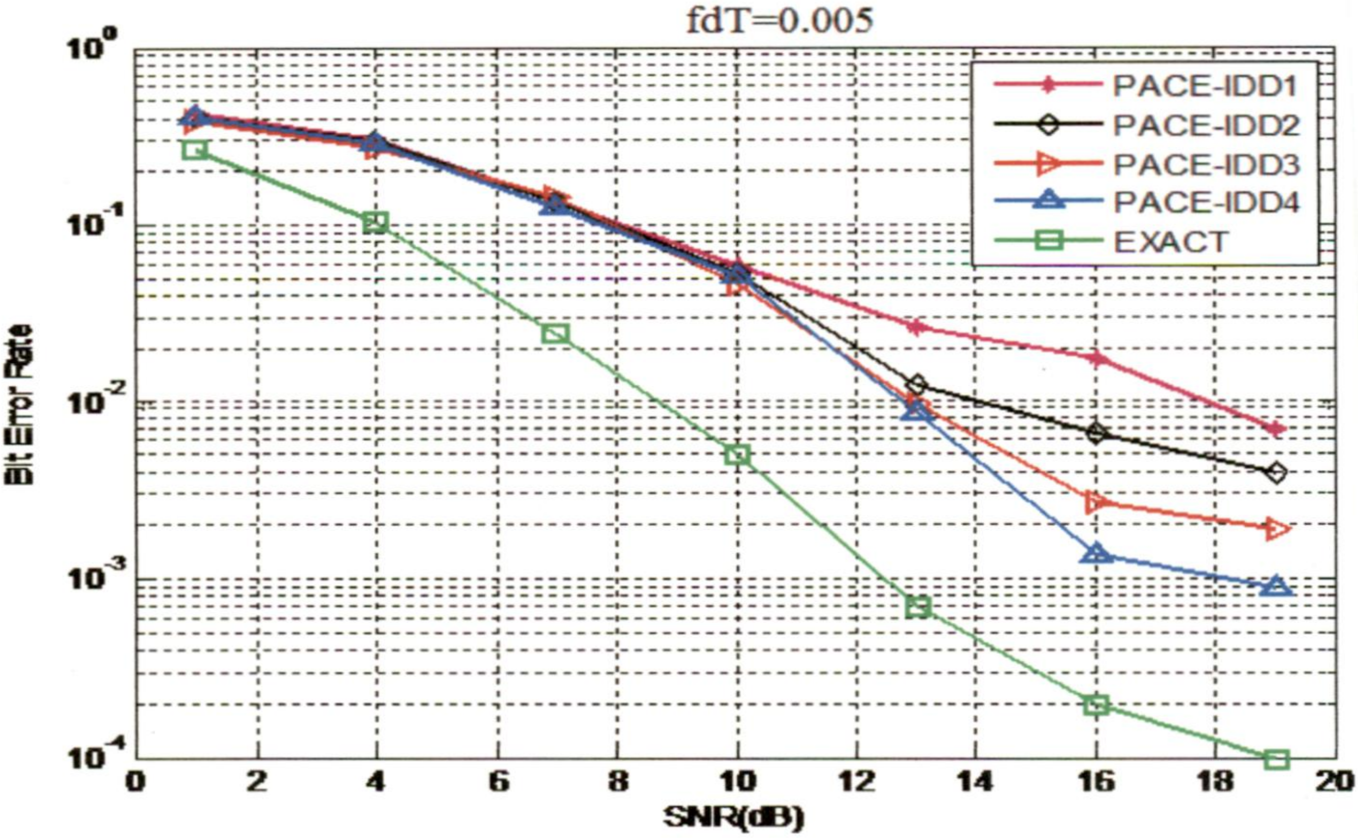


Figure 4.6. Comparison of BER performance for pilot based channel estimation technique with different IDD iterations in time varying fading environment for MIMO-OFDM systems($f_d T$ =0.005).

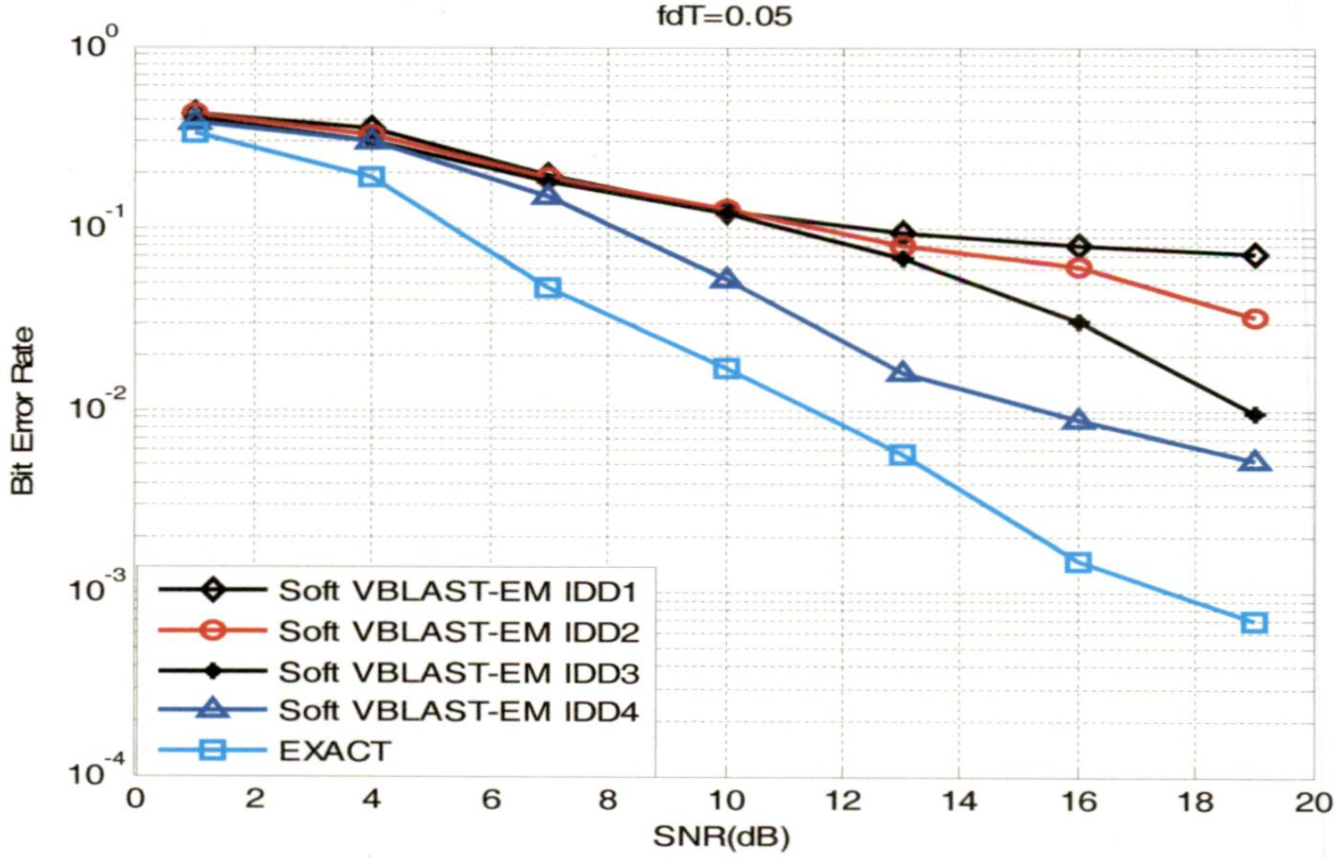


Figure 4.7. Comparison of BER performance for soft VBLAST-EM based channel estimation technique with different IDD iterations in time varying fading environment for MIMO-OFDM systems($f_d T$ =0.05).

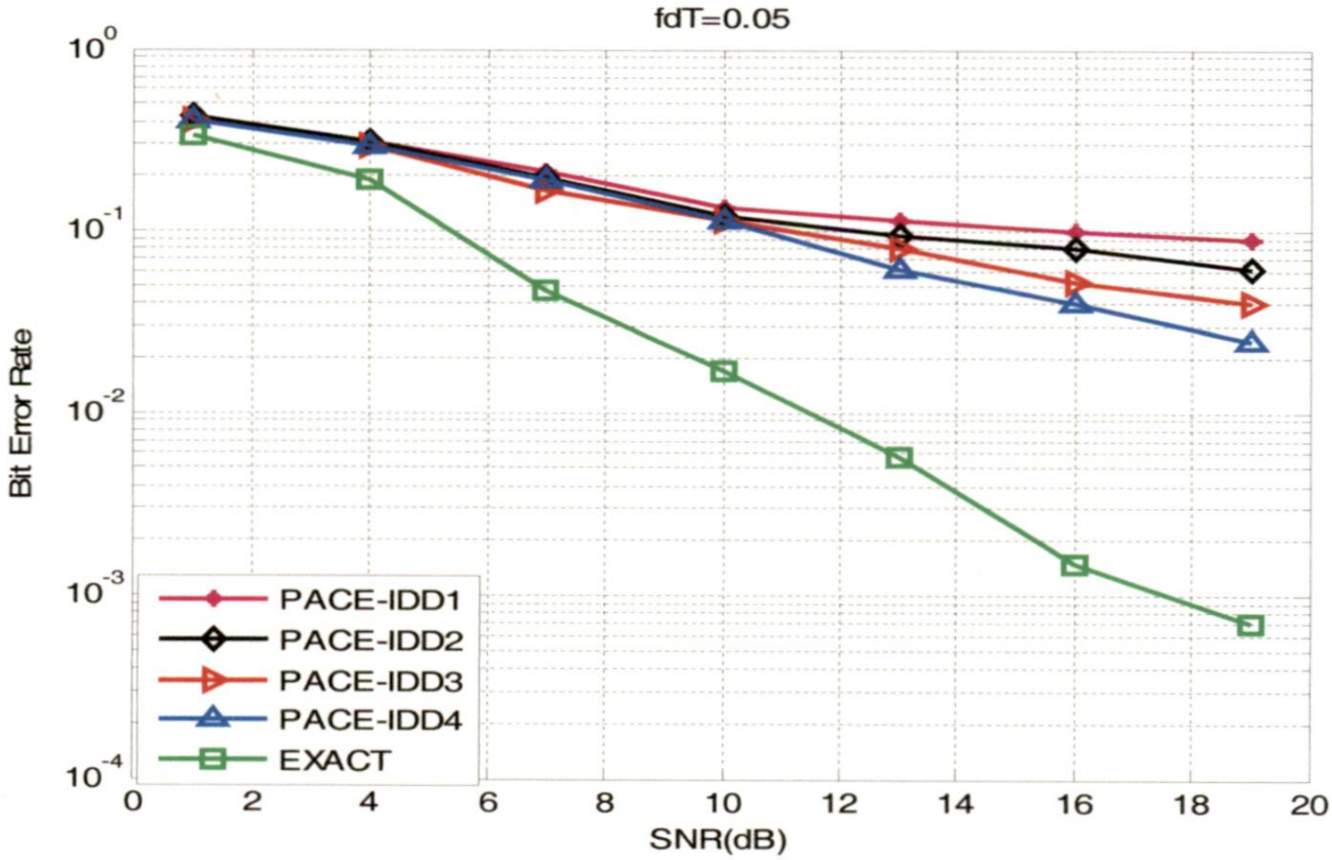


Figure 4.8. Comparison of BER performance for pilot based channel estimation technique with different IDD iterations in time varying fading environment for MIMO-OFDM systems(f_dT =0.05).

Chapter 5
CONCLUSIONS

In many parameter estimation problems, the situation is complicated because direct access to the data, required to estimate the parameters is impossible or some of data are missing. The ideal solution to deal with these problems is EM algorithm. The Maximum Likelihood estimate of channel impulse response is obtained by using channel statistics via EM algorithm. Due to the effective convergence of EM algorithm, it can be invariably applied to a variety of applications, like channel estimation, signal detection, speech recognition etc. This dissertation work is aimed at the channel estimation problems via EM algorithm in systems like OFDM, MIMO-OFDM and VBLAST MIMO-OFDM. Iterative detection and decoding improves both the detection and the interference cancellation performance by utilizing the decoder output. The conclusions drawn based on the simulation results are as follows:

EM based channel estimation for OFDM systems

We have used EM and EM-MMSE techniques for channel estimation of OFDM system in a Rayleigh multipath fading channel with both stationary and time varying environment. As simulation results of OFDM system show, EM-MMSE technique performs well when compared to the EM technique. In Rayleigh multipath fading with stationary environment, it is seen that, the BER performance for both techniques improves to within 0.3 dB of exact CSI curve at high SNRs and the number of iterations required for EM-MMSE technique is reduced by a factor of almost 6 as compared to EM method. In time varying environment, the number of iterations required for EM-MMSE technique is reduced by a factor of almost 6 as compared to EM method.

EM based channel estimation for MIMO-OFDM systems

We have used PACE and hard VBLAST-EM techniques for channel estimation of MIMO-OFDM system in a Rayleigh multipath fading channel with time varying environment. The estimates from PACE are used to initialize the hard VBLAST-EM based channel estimation technique. As simulation results of MIMO-OFDM system show, the MSEE performance of hard VBLAST-EM improves by 1-2dB and 2-3 dB as compared to PACE curve at high SNRs for Doppler value of f_dT=0.005 and f_dT=0.05 respectively. The BER performance improves to within 8-9 dB of exact CSI curve at high SNRs performance for Doppler value of f_dT=0.005.

Iterative Detection and Decoding for MIMO-OFDM using soft VBLAST-EM algorithm

We have used soft VBLAST-EM technique with IDD structure for channel estimation of MIMO-OFDM system in a Rayleigh multipath fading channel with time varying environment. The estimates from PACE are used to initialize the soft VBLAST-EM based channel estimation technique. The MSEE performance of soft VBLAST-EM improves by 2-3 dB as compared to PACE curve at high SNRs for Doppler value of f_dT=0.005. It may be seen that as the number of iterations of IDD block increases, the BER performance increases. The BER performance of soft VBLAST-EM technique improves to within 6-7 dB and 3-4 dB of exact CSI curve at high SNRs as iterations of IDD block increases to 4 for Doppler value of f_dT=0.05 and f_dT=0.005 respectively.

Future work

The performance of the system can be improved by using the soft decisions on the received symbol instead of hard decisions. In the IDD block, the Viterbi decoder can be replaced by a MAP decoder to improve the performance at the cost of increased computational complexity. It is possible to avoid matrix inversion by estimating the channel in frequency domain instead of time domain. However this can degrade the performance. It is also possible to design a joint iterative channel estimation and detection, which combines soft VBLAST-EM channel estimation and IDD tasks in a single block. By using iterative procedure the performance can be improved. The VBLAST detection algorithm can be replaced by QRD-M algorithm, for achieving the improved performance and decrease in the computational complexity [29]. The unbiased EM (UEM) can be designed to unbias the EM estimates which can be used in place of EM [16].

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