Channel Estimation in DS-CDMA System based on Quantum Constraints

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Abstract:- A system model for DS-CDMA (Direct Sequence Code Division Multiple Access) is described in its basic form and performance measure based on Mean Square Error (MSE) and Symbol Error Rate (SER) under Additive White Gaussian Noise is performed. For measuring the performance of DS-CDMA receivers, the channel estimate plays for a crucial role and hence the channel estimation for DS-CDMA is considered. We describe the channel estimation based on the time domain channel statistics, using a general model for a slow fading channel. The investigation on the performance of Least Square estimator (LS) and Minimum Mean Square Error estimator (MMSE) in asynchronous DS-CDMA linear receiver is studied. The investigation studies the effect of MSE and SER with different modulation scheme employed in it and their analysis of modulated effect are taken into comparison. The result shows that the proposed MMSE channel estimator, exhibiting the best trade-off between LS and MMSE estimation error components.

Keywords: Orthogonality, Gaussian Channel, Covariance, Spread Spectrum, Mean Square Error

1. Introduction

The wireless channel in mobile radio poses a great challenge as a medium for reliable high speed communications. When a radio signal is transmitted through a wireless channel it suffers various types of distortions. Hence, the receiver obtains a linear superposition of the signals transmitted by all the users, attenuated by arbitrary factors and delayed by an arbitrary amount. However the synchronous transmitted signals have a common offset with respect to the arbitrary receiver clock.

The problem of channel estimation in this case involves estimation of this single offset as well as the common signal attenuation faced by the transmitted signals for all the users. In the presence of a number of interfering users in the channel, channel estimation is not a trivial task, due to the near-far effect. The near-far problem arises when the signals from the different users arrive at the receiver with widely varying power levels. So a signal with lower power cannot be detected correctly due to the presence of other signals with higher powers. The near-far problem has been shown to severely degrade the performance of standard single user techniques (e.g., matched filters, correlators, etc.) in conventional CDMA systems; as such systems treat the interfering users as noise.

In [1] chaitali addressed the problem of channel estimation for CDMA communication and explains that in the presence of multiple sensors we can come to a conclusion that the structure of interfering users and working in a multipath environment shall be exploited in multiuser techniques for channel parameter estimation .In[2] Michael Meyer takes into consideration several concepts the channel estimation in DS-CDMA and compares their performances by simulation results . from this it is evident that the receiver knows the corresponding spreading sequence .Therefore this sequence can be used for correlative channel estimation

In [3] the usage of Moving average (MA) FIR filter as the Channel Estimation Filter(CEF) is taken into consideration as it is simple to implement and can provide relatively good receiver performance. In addition to that the Result also shows that the use of the proposed ACE can provide the receiver performance comparable to that of Weiner CEF. In [4] Xenofan explains the existence of blind methods and their loss from high computational complexity (due to large SVDs) and sensitivity to accurate knowledge of the noise subspace rank, the proposed method overcomes both problems. *It also* approaches (Singular Value Decomposition and least squares) are also extended to accommodate for synchronization with respect to the user of interest.

In [5] Buzzi says that the adaptive algorithm outperforms decision-directed RLS algorithm in MMSE multiuser receivers. In addition [6] Buzzi also describes that new receivers outperform the classical ones in terms of error probability and near-far resistance. And it is confirmed that new receivers can accommodate twice the number of users accommodated by the classical with reference to CDMA system with deterministic spreading codes.In [7] Fazel analyses the power to sway effects of the non-linearity due to high power amplifier in Multi Carrier(MC) CDMA scheme using BPSK modulation. The obtained results are compared to those with the classical BPSK modulated DS-scheme

In [8] Xiangliu Precises bit-error-ratio (BER) analysis of an asynchronous QPSK-modulated direct-sequence code-division multiple-access system using random quaternary spreading sequences for transmission over Rayleigh channels is performed based on the characteristic-function approach. In[9] frequency tracking characteristics of a complex-coefficient adaptive Infinite-Impulse Response (IIR) notch filter used for suppression of Narrow-Band Interference (NBI) with a randomly-varying frequency in a Quadri Phase Shift keying (QPSK) modulated direct-sequence code-division multiple-access (DS-CDMA) communication system has been analyzed.

In [10] it is clear that the power spectra of continuous phase modulation schemes are narrower than BPSK schemes, and hence a larger processing gain should be used for overall bandwidth after spreading .In [11] Manish analyses the bit error probability of DSCDMA as the BPSK shows improved performance in the probability of errors. It can also be understood from here that the coding further improves DSCDMA system when compared without coding .On taking [12] in consideration the performance of of $\pi/2$ -shift BPSK and conventional BPSK CDMA system is taken into comparison over multipath Rayleigh fading channel.

In [13] the problem of optimizing the channel estimate for a wideband DS-CDMA rake receiver. A simplified adaptive least squares scheme is proposed as a channel estimator, with only one adjustable parameter, the averaging window size has been described. Then, the mean squared error of the channel estimate is analytically extracted. An MMSE channel estimator is finally proposed, exhibiting the best trade-off between the two antagonistic estimation error components.

In [14] Yonina borrows the formation and principles of quantum mechanics and other interesting axioms and constrains for quantum signal processing with applications in areas ranging from frame theory, quantization and sampling methods for detecting parameter estimation , co-variance shaping and multiuser communication systems. From his words one could derive an efficient covariance shaping multiuser receiver for suppressing interference

In [15] it is clear that the tracking of the fading radio channel is required for the use of multi-amplitude signalling schemes in wireless OFDM systems. In further it explains the channel estimation based on time-domain channel statistics. It also presents a method for compromising the modifications between the complexity and performance of MMSE and LS estimators. Depending upon estimator complexity, up to 4 dB in SNR can be gained over the LS estimator. In [16] Sanjitlal describes the channel estimation based on time domain channel statistics. MMSE and LS estimators by using a general model for a slowly fading channel,. The mean square error and symbol error rate for a BPSK system is presented by means of simulation results.

The idea we propose in this paper overcomes drawbacks reported above for the already existing schemes. In designing channel estimators for wireless OFDM systems the first and the foremost problem is the design of an estimator with both low complexity and good channel tracking ability. Direct Sequence Spread Spectrum (DS-SS) Code Division Multiple Access (CDMA) techniques using multipath diversity over multipath fading channels have received considerable attention for mobile communications due to their obtainable satisfactory capacity.

Although DS/SS/CDMA has low power spectral density, simultaneous transmissions may cause interference to the systems lying in adjacent frequency bands if the spectrum is not well trimmed out. Hence the bandwidth limitation of transmitted signal is essential. The estimations for the block-type pilot arrangement can be based on least square (LS), minimum mean-square error (MMSE). In order to obtain high power efficiency of mobile transmitters often operate near saturation regions exhibiting nonlinear distortion. The bandwidth limitation by a filter causes large envelope variations and high power efficient amplifiers generate spectral components outside the allocated bandwidth because of their nonlinearity and thus cause interference to adjacent frequency bands.

To avoid the effect of nonlinear distortion, modulation methods which do not introduce large fluctuations in the envelope after filtering are highly appreciated. BPSK and QPSK signals are considered to have smaller envelope fluctuations because it has smaller maximum phase transition than the others. By mathematical analysis and simulation the performance of the DS-CDMA system in presence of interfering users in AWGN is evaluated. We provide plots of MSE and SER for various conditions to illustrate the effect of error components. In addition simulation and analytical results are presented to compare the performance of system in situation with different modulation schemes.

2. Experimental Procedure

We will considered a system x_k is a transmitted symbol, g(t) is a channel impulse response, ñ(t) is the white complex Gaussian channel noise and y_k are the received symbols. The transmitted symbols x_k are taken from a multi-amplitude signal constellation. The D/A and A/D converters contain ideal low-pass filters with bandwidth $1/T_s$, where $T_s$is the sampling interval. A cyclic extension of time length T_G is used to eliminate inter-block interference and preserve the orthogonality of the tones.

We treat the channel impulse response g(t) as a time limited pulse train of the form in (1),

$$g(t) = \sum_m a_m \delta(t - \tau_m T_{s)} \tag{1}$$

where the amplitude a_m are complex valued and $0 \le \tau_m T_s \le T_G$, i.e., the entire impulse response lies inside the guard space. The system is then modeled using the N-point discrete-time Fourier transform (DFT_N) as

$$Y = DFT_N(IDFT_N(x) * \frac{g}{\sqrt{N}} + \tilde{n} \tag{2}$$

where * denotes cyclic convolution=$[x_0\ x_1 \ldots x_{N-1}]^T$,y=$[y_0 y_1 \ldots y_{n-1}]^T$, ñ=$[\tilde{n}_0\ \tilde{n}_1 \ldots \tilde{n}_{N-1}]^T$is a vector of i.e. complex Gaussian variables, and g=$[g_0\ g_1 \ldots g_{N-1}]^T$ is determined by the cyclic equivalent of sin-functions. The vector $g/\sqrt{N}$ is the observed channel impulse response after sampling the frequency response of $g(t)$, and

$$g_k = \frac{1}{\sqrt{N}} \sum_m a_m e^{-j\frac{\pi}{N}(k+(N-1))} \frac{\sin(\tau m)}{\sin(\frac{\pi}{N}(\tau m - k)} \tag{3}$$

The validity of the cyclic model described by (2) and (3) depends on how well the objective of the guard space is met, i.e., how well it eliminates inter-block interference. If the delay $\tau_m$is an integer, then all the energy from α_m is mapped to tap $g_{\tau m}$. However, for a non-*T*-spaced pulse, i.e., if $\tau_m$is not an integer, its energy will leak to all taps g_k. It illustrates this leakage for a special case. Notice that most of the energy is kept in the neighborhood of the original pulse locations. The system described by (2) can be written as a set of *N* independent Gaussian channels,

$$Y_k = h_k x_k + n_k, \qquad k = 0,1,2 \ldots N-1 \tag{4}$$

where h_k is the complex channel attenuation given by

$h = [h_0, h_1 \ldots h_{N-1}]^T = DFT_N(g)$ and

$n = [n_0, n_1, \ldots n_{N-1}]^T = DFT_N(n)$

is an complex zero-mean Gaussian noise vector. As a matter of convenience, we write (4) in matrix notation

$$y = XFg + n \tag{5}$$

where X is a matrix with the elements of **x** on its diagonal and

$$F = \begin{bmatrix} WN0o & \ldots\ldots & WN0(N-1) \\ . & & \\ . & & \\ WN(N\_1)0\ldots\ldots & & WN(N\_1)(N-1) \end{bmatrix} \tag{6}$$

where **X** is a matrix with the elements of **x** on its diagonal and

$$W_N{}^{nk} = \frac{1}{\sqrt{N}} e^{-j\frac{2\pi nk}{N}} \tag{7}$$

2.1 DS-CDMA Communication System

In Code Division Multiple Access (CDMA) system uses the same bandwidth for all users to transmit the data simultaneously known as "spread spectrum systems". is spread using a code This technique uses the uncorrelated code to spread the frequency spectrum of a data-signal thereby increases the bandwidth occupancy to much higher level. The uncorrelated codes have low cross-correlation values and are unique to every user and help the receiver to select the desired signal.

Direct sequence signals are generated by their modulating a carrier with a code sequence. In a DS-CDMA communication system the incoming information signal is not in a digital format, it is digitized and modulo-2 added to a higher speed code sequence. The combined information and code then are used to modulate on RF carrier using BPSK modulation technique. As high speed code sequence dominates the modulating function, it determines the RF signal bandwidth and gives rise to the spread spectrum signal.

Spread spectrum is a communication technique wherein the transmitted signal is spread in bandwidth before transmitting through the

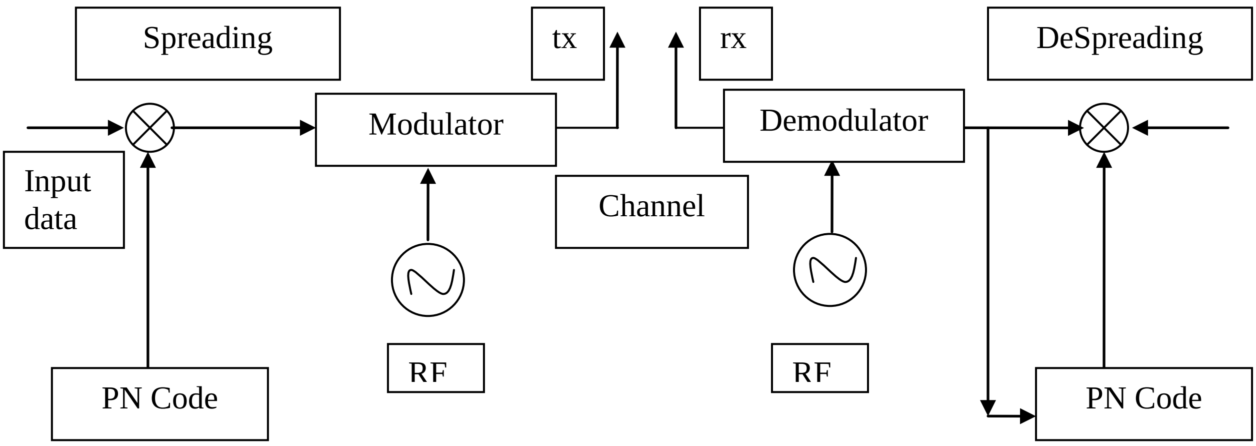

Fig 1.DS-CDMA system

channel and it is despread at the receiver end with the same bandwidth. The spreading and despreading would be transparent if there is no narrowband band interference. That is after despreading the received signal would be identical to the transmitted signal prior to spreading, but its presence provides substantial advantage to do spreading and despreading. The despreading operation at the receiver shrinks the desired signal back to its original bandwidth, because the interference is introduced after the transmitted signal is spread, at the same time it spreads interference (undesired signal) in bandwidth by the same amount, thus reducing its power spectral density (PSD). This, in turn, serves to diminish the effect of the interference on the receiver performance, which depends on the amount of in the spread bandwidth.

3. Channel Estimation

The transmitted symbols x_k, appearing in the estimator expressions, are either training symbols or quantized decision variables in a decision-directed estimator. Error propagation in the decision-directed case is not treated in this paper. The channel estimation methods can be divided into two groups: Non-blind methods where a training sequence is inserted into the transmission and blind methods that exploit various statistical properties of the transmitted signals to carry out channel estimation in the receiver without access to the symbols being transmitted.

3.1. Least square estimator

The least square methods (LSM) is probably the most popular technique in statistics. First, most common estimators can be castled within this framework. The squared error and the squared estimated quantity can be added when the error is independent of an estimated quantity. The mathematical tools and algorithms involved in LSM (Eigen decomposition, Derivatives, and Singular value decomposition) have been well studied for a relatively long time. The method of least squares is about estimating parameters by minimizing the squared discrepancies between observed data. The variation in one variable, called the response variable *Y*, can be partly explained by the variation in co variables known as regression problem

The least squares criterion is a computationally convenient measure of fit. It corresponds to other estimation when the noise is normally distributed with equal variances. No probabilistic assumptions required. The performance highly depends on the noise. A generic estimation problem that has been studied extensively in the literature is that of estimating the unknown deterministic parameters **x** in the linear form,

$$Y = Hx + w \tag{8}$$

where H is known n x m matrix, and w is a zero-mean random vector with covariance **C***w*. For simplicity of exposition we assume that rank (H) = *m*, the results extend in a straight forward way to the case in which rank (H) < *m*. An important special case of a non full-rank model is considered in section

A common approach to estimating the parameters **x** is to restrict the estimator to be linear in the data **y**, and then find the linear estimate of **x** that result in an estimated data vector $\hat{\mathbf{y}}$ that is as close possible to the given data vector **y** in a (weighted) LS sense, so that $\hat{\mathbf{y}}$ is chosen to minimize the total squared error in the observations.

The Gauss-Markov theorem states that the weighting matrix that leads to an unbiased estimator of **x** with minimum variance is $\mathbf{C}^{-1}w$. Thus, the LS estimate $\tilde{x}_{LS} = G_y$ is chosen to minimize the total squared error.

$$\varepsilon_{LS} = (y - HG_y) * C^{-1}{}_w (y - HG_y) \tag{9}$$

and is given by

$$\tilde{x}_{LS} = (H * C^{-1}{}_w H)^{-1} H * C^{-1}{}_w y \tag{10}$$

The LS method is widely employed in diverse fields, both as an estimation criterion and as a method for parametric modeling of data. Numerous extension of the LS method has been previously proposed in the literature. The Total LS method, first proposed by Golub and Van Loan in ,assume that the model matrix H may not be know exactly and seeks there parameters x and the minimum perturbation to the model matrix that minimize the LS error.

The extended method proposed by Yeredorin seeks parameter and some presumed underlying data that together minimize a weighted combination of model errors and measurement errors. In both of these extensions it is assumed that data model does not hold perfectly, either due to the errors in H or errors in the data y.

In our method we assume that the data model holds i.e., $Y = Hx + w$ with H and y known exactly, and our objective is to minimize the error between x and the estimate of x. In many cases the data vector y is not very sensitive to changes in x, so that a large error in estimating x may translate into a small error in estimating the data vector y, in which case the LS estimate may result in a poor estimate of x.

This effect is especially predominant at low to moderate SNR, where the data vector y is typically affected more by the noise than changes in x; the exact SNR range will depend on the properties of the model matrix H. A difficulty often encountered in this estimation problem is that the error in the estimation can have a covariance structure with a very high dynamic range.

The LS estimator for the cyclic impulse response g minimizes $(y - XFG)^H (y - XFg)$ and generates,

$$\hat{H}_{LS} = FQ_{LS} F^H X^H y \tag{11}$$

$$Q_{LS} = (F^H X^H xF)^{-1} \tag{12}$$

Note that $\hat{h}_{LS}$ also corresponds to the estimator structure. Since (11) reduces to $\hat{h}_{LS} = X^{-1}y$, the LS estimator is equivalent to what is also referred to as the zero-forcing estimator. The MMSE estimator suffers from a high complexity, whereas the LS estimate has a high mean-square error. In the next section, we will address these drawbacks and modify both estimators.

3.2 Minimum mean square estimator

The introduction of an error criterion, that measures in a probabilistic sense, which means the error between the desired quantity and our estimate of it. We focus mainly on choosing our estimate to minimize the expected or mean value of the square of the error, referred to as a minimum mean-square-error (MMSE) criterion. We consider the MMSE estimate without imposing any constraint on the form that the estimator acquires. With the advent of high-throughput genomic and proteomic technologies we restrict the estimate to be a linear combination of the measurements, a form of estimation that we refer to as linear minimum mean-square-error (LMMSE) estimation.

In this investigation, we place classifier error estimation into the framework of optimal mean square error (MSE) signal estimation in the presence of uncertainty, results in a Bayesian approach. This error estimation is based on a parameterized family of feature-label distributions with the prior distribution of the parameters governing the choice of feature-label distribution. These Bayesian error estimators are chosen to be best when averaged over some distributions, unbiased when averaged over all samples, and analytically address a trade-off between modeling assumptions and minimum mean square error.

Properties, provide closed-form analytic estimator representation for discrete classifiers with both non-informative and informative prior distributions, and examine the performance and robustness of the MMSE error estimator via simulations. For both the discrete and Gaussian cases, the MMSE error estimator has especially good performance for distributions having moderate true errors

The MMSE criterion may not be meaningful in such hypothesis testing problems, but we can for instance aim to minimize the probability of an incorrect inference regarding which hypothesis actually applies.

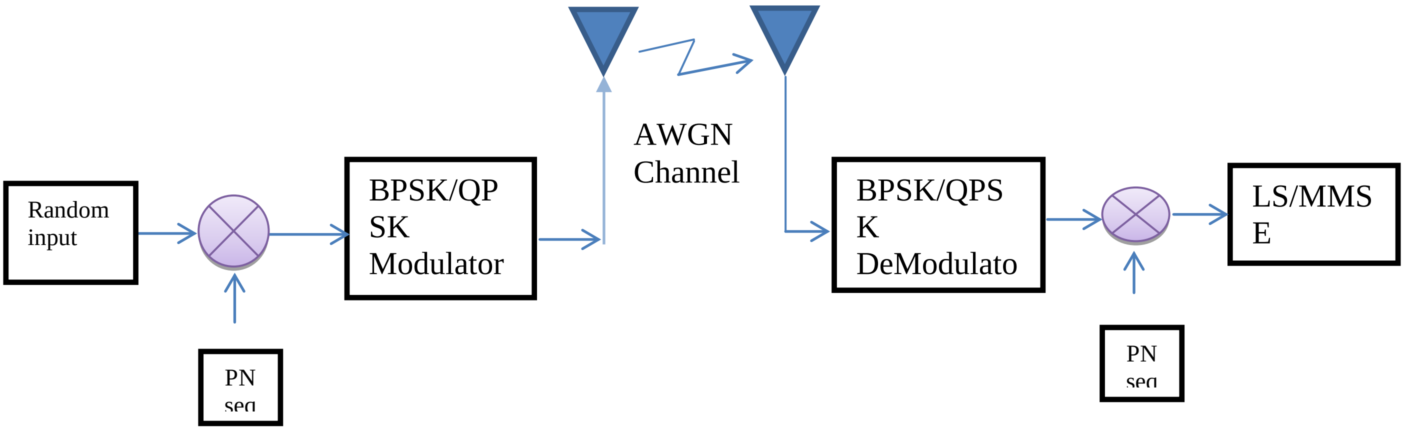

Fig 2. DS –CDMA System

If the channel vector **g** is Gaussian and uncorrelated with the channel noise **n**, the MMSE estimate of **g** becomes [9]

$$\hat{g}_{mmse} = R_{gy} R_{yy}^{-1} y \qquad (13)$$

where

$R_{gy} = E\{gy^H\} = R_{gg} F^H X^H$

$R_{yy} = E\{yy^H\} = XFR_{gg} F^H X^H + \sigma^2{}_n I_N$ are the cross covariance matrix between g and y and the auto-covariance matrix of y. Further, R_{gg} is the auto covariance matrix of g and $\sigma^2{}_n$ denotes the noise variance E{$|n_k|^2$}. These two quantities are assumed to be known. Since the columns in F are orthonormal, $\hat{g}_{mmse}$ generates the frequency-domain MMSE estimate $\hat{h}_{mmse}$ by

$$\hat{h}_{mmse} = F\hat{g}_{mmse} = FQ_{mmse} F^H X^H y \qquad (14)$$

where Q_{MMSE} can be shown to be

$$Q_{mmse} = R_{gg}[(F^H X^H XF)^{-1} \sigma_n^2 + R_{gg}]^{-1} F^H X^H XF)^{-1} \qquad (15)$$

This MMSE channel estimator (15) has the form. If g is not Gaussian, $\hat{h}_{mmse}$ is not necessarily a minimum mean-square error estimator. It is however the best linear estimator in the mean-square error sense. In either case (g, Gaussian or not) we will denote the channel estimate as $\hat{h}_{mmse}$.

For low SNRs, this approximation effect is small compared to the channel noise, while it becomes dominant for large SNRs. The curves level out to a value determined in the energy of the taps. MMSE estimator reduces the mean square error for a range of SNRs compared to LS estimator.

The symbol error rate (SER) curves shown in the figure are based on the mean square error of the channel estimation shown in previous section. These formulae are used to find the symbol error rate of a system, given the noisy estimate of the channel.

4. Results and Discussion

In this section we discuss the performance analysis of DS-CDMA system which were obtained in our simulation process using matlab version 7.1.The performance of the estimators are being discussed in terms of the signal to noise ratio versus symbol error rate and signal to noise ratio versus mean square error. In DS-CDMA system, random data sequence with data length N=64 is given as input with BPSK/QPSK modulation scheme employed in it The mean square error and symbol error rate performance of DS-CDMA systems with both least square and minimum mean square error (MMSE) estimation are carried out.

In DS-CDMA system, random sequence input of length N=64 is given through pseudo-random noise generator that is simply a binary linear feedback shift register, consisting of XOR gates and a shift register and random PN sequence code are generated. It has ability to create an identical sequence for both the transmitter and the receiver properties of a noise-like randomness bit sequence.

PN sequences have characteristics such as nearly equal number of zeros and ones and Low correlation between shifted versions of the sequence, Low cross-correlation with other user signals (interference) and noise. Then input signal is spreaded by using PN sequence.

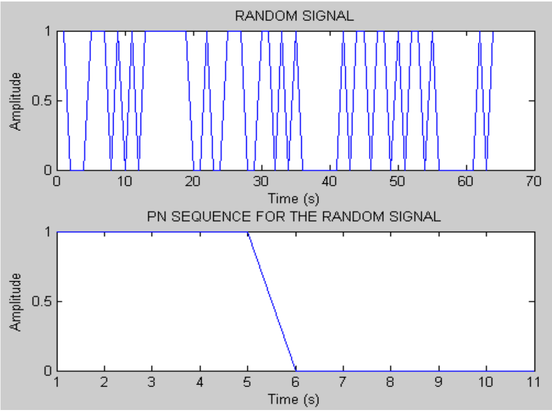

Fig 3(a) Random Input Signal
Fig 3(b) Random PN Sequence

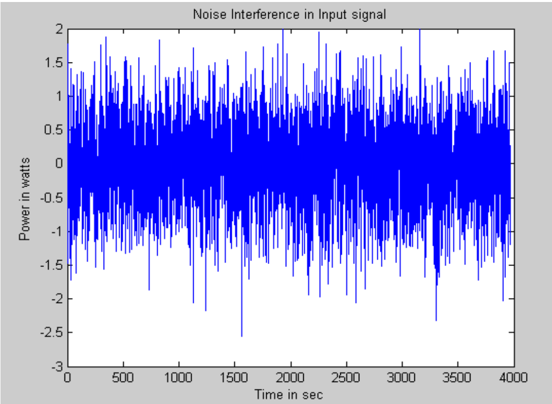

Fig 4. Additive White Gaussian Noise

In QPSK, the data bits to be modulated are grouped into symbols, each containing two bits, and each symbol can take on one of four possible values: 00, 01, 10, or 11. During each symbol interval, the modulator shifts the carrier to one of four possible phases corresponding to the four possible values of the input symbol. Quadrature Phase Shift Keying is effectively two independent BPSK systems (I and Q), and therefore exhibits the same performance but twice the bandwidth efficiency. Quadrature Phase Shift Keying can be filtered using raised cosine filters to achieve excellent out of band suppression.

In DS-CDMA Communication Systems, communication channels are often modeled with Additive White Gaussian Noise (AWGN). The adjective 'additive' describes the interaction that happens between the noise interact with another signal during collision. When AWGN comes in contact with a user signal, the real and imaginary amplitude components of the two signals add up and form a new signal. This demodulation technique is to extracting original information-bearing signals from a modulated carrier-wave. This demodulation block does the reverse operation of BPSK, QPSK modulation at the transmitter end to get the original signal. The receiver acquires the received code and phase locks its own code to it. The received signal is correlated with the generated PNcode, extracting the information data.

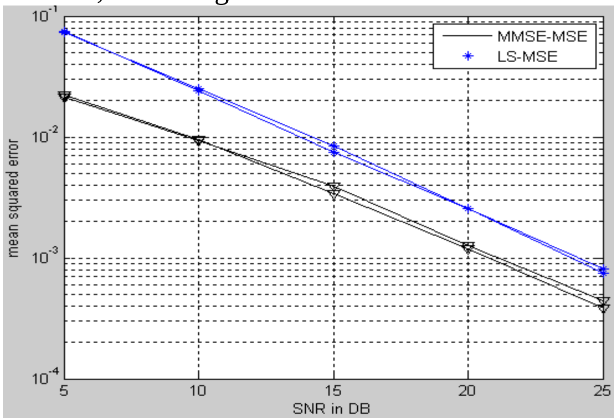

Fig 5. Plot of SNR versus MSE for a DS-CDMA with LS and MMSE

Figure 5 shows the mean square error versus SNR for the MMSE, LS estimators is plotted for the proposed block-type pilot channel estimation schemes over a AWGN channel with a bandwidth of 220 kHz, DFT size N=64 BPSK,QPSK modulation. In this figure, the legends LS, MMSE present the estimators based on LS, MMSE respectively, without the decision feedback. For low SNR's this approximation effect is small compared to the channel noise, while it becomes dominant for large SNR's..

Table 1 MSE vs SNR

SNR	SER in LS		SER in MMSE	
	BPSK	QPSK	BPSK	QPSK
5	0.0519	0.0262	0.0260	0.0131
10	0.0283	0.0150	0.0141	0.0076
15	0.0172	0.0090	0.0086	0.0045
20	0.0108	0.0056	0.0053	0.0028
25	0.0078	0.0040	0.0039	0.0020

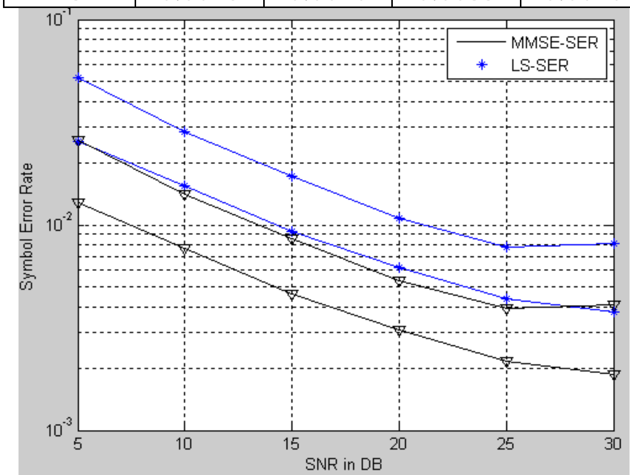

Fig 6. Plot of SNR versus SER for an DS-CDMA with MMSE and LS estimator

Figure 6 shows that the symbol error rate (SER) versus the average SNR is plotted for the proposed block-type pilot channel estimation schemes over a AWGN channel with a bandwidth of 220 kHz, DFT size N=64 BPSK,QPSK modulation. In this figure, the legends LS, MMSE present the estimators based on LS, MMSE respectively, without the decision feedback. The MMSE estimator yields the best performance, and LS yields the worst.

Table 2. SER vs SNR

SNR	MSE in LS		MSE in MMSE	
	BPSK	QPSK	BPSK	QPSK
5	0.0736	0.0744	0.0214	0.0232
10	0.0250	0.0239	0.0093	0.0096
15	0.0084	0.0074	0.0039	0.0032
20	0.0026	0.0026	0.0013	0.0012
25	0.0009	0.0007	0.0005	0.0004

5. Conclusion

The algorithm of LS estimator is very simple, As LS algorithm does not require correlation function calculation nor does it require matrix inversion. MMSE estimator is complex. As MMSE algorithm requires both correlation function calculation and matrix inversion. From the results it is clear that MMSE estimator provides better performance than LS estimator in terms of mean square error (MSE) and symbol error rate (SER) whereas implementation of LS algorithm is much easier than MMSE algorithm.

References:

[1]Chaitali Sengupta, “Algorithms and Architectures for Channel Estimation in Wireless CDMA Communication Systems” Thesis, Rice University, Houston, Texas, December,1998.pp-1-152.

[2]Volker Kiihn and Michael Meyer,” Correlative Channel Estimation in DS-CDMA systems”, Third Annual Wireless Symposium No 41, 2005, pp-279-284

[3]Ji-Woong Choi& Yong Hwan,” Efficient Channel Estimation in DS-CDMA systems” IEICE Trans on Communications, No.6, 2004, pp.1470-1478

[4]Xenofon G. Doukopoulos and George V. Moustakides,” Blind Channel Estimation for DS-CDMA”, INRIA Rennes, March; 2003.

[5]Stefano Buzzi, and Marco Lops,” A New Family of MMSE Multiuser Receivers for Interference Suppression in DS/CDMA Systems Employing BPSK Modulation”, IEEE Transactions on communication, No 49, 2003 pp.154-167.

[6] Stefano Buzzi, and Marco Lops,” Performance Analysis for the Improved Linear Multiuser Detectors in BPSK-Modulated DS-CDMA Systems” IEEE Transactions on communication, No 51, 2003, pp-37-42.

[7]Aloys N. Mvuma, “QPSK DS-CDMA System over Rayleigh Channel with a Randomly-Varying Frequency Narrow-Band Interference: Frequency Tracking Analysis**”,** Scientific Research open Access, No.3, 2010, pp-243-249.

[8] *David K. Asanoy, TatsujiHayashiy and Ryuji,”* Modulation and Processing Gain Tradeoffs in DS-CDMA Spread Spectrum Systems”,ISSSTA '1998,No1,pp-1-9.

[9] Pulin Patel and Jack Holtzman, “Analysis of Simple successive interference cancellation scheme in DS-CDMA system” IEEE journal on selected areas in communication, 1994, No 5, pp-796-807.

[10].Georgiadis, “MMSE Optimization for LS Channel Estimation in Wideband DS-CDMA Rake Receivers”, IEEE International Conference on Acoustics, Speech and Signal processing, No 4 2006, pp-4-6.

[11]Manish Rai and Inderpreet Kaur, “Performance Improvement of DS-CDMA Wireless Communication Network with Convolutionally Encoded OQPSK Modulation Scheme” IJAET, March 2011, pp-28-33.

[12]Fazel and Kaiser, “Analysis of Non-Linear Distortion on MC-CDMA”, IEEE International conference on communication, No.2, 1998,pp-1028-1034.

[13]Xiang Liu,” Precise BER Formulas for Asynchronous QPSK-Modulated DS-CDMA Systems Using Random Quaternary Spreading Over Rayleigh Channels”, IEEE Transactions on Vehicular Technology, 2008, No.1,pp-239-242.

[14]Yonina.C. Eldar, “Quantum signal processing”, IEEE Signal processing, 2002, No 6, pp-12-32.

[15]YushiShen and Ed Martinez, “On Channel Estimation in OFDM Systems” Freescale Semiconductor, Inc. 2006.

[16]BarnaliDey,Awanish Kumar and Prashant Kumar, “Channel Estimation using LS and MMSE Algorithm”, ISDMISC, 2011,No 8,pp-32-35.