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COMPLEXITY REDUCED CHANNEL ESTIMATION IN WIMAX ENVIRONMENT FOR MIMO–OFDM SYSTEM

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Abstract

Multiple Input Multiple Output (MIMO) and Orthogonal Frequency Division Multiplexing (OFDM) are considered to be major methods for the ensuing high performance in next generation mobile communications. The undesirable effects on the transmitted signals need to be addressed and eliminated to improve the capacity of the systems. These effects depend on the physical properties of the channel. Hence, there is a need to provide perfect estimate of the channel to counteract these effects and thereby delivering precise base-band processes at the receiving end of the system such as signal demodulation and decoding. In this paper, the channel between multiple antenna elements are investigated and analysed for optimum technique with less complexity and less power requirement to estimate the characteristics of the channel. The bit error rate (BER) and normalised mean square error (NMSE) of the channels in MIMO-OFDM systems are examined for different channel tracking techniques. The simulation results are measured to investigate the working of the system model with different algorithms over Worldwide Interoperability for Microwave Access channel. An efficient QRD method is suggested in this paper based on the available system resources and specifications.

Keywords: MIMO-OFDM, Channel Estimation, WiMAX, QR Decomposition, BER, NMSE, Computational Complexity.

1. Introduction

The widespread development of multimedia based applications propelled the growth of wireless system technologies with high data rate capability. OFDM is a multi-carrier modulation (MCM) technique, commonly known as simultaneous MFSK, used extensively in high speed digital communication environments.

Nomenclatures

K	*Correlation factor*
H	*Channel matrix*
N_r	*Number of receiving antennas*
N_t	Number of transmitting antennas
R_H	Channel correlation matrix
S	Transmitted signal
U	*Cyclic prefix added signal*
W	AWGN noise
Y	Received signal (ISI free)

Greek Symbols

$\mathcal{J}_{\text{RMMSE}}$	Mean square error in RMMSE
$\mathcal{J}_{\text{LS}}$	Mean square error in LS
σ^2	Received noise power

Abbreviations

BER	Bit Error Rate
FFT	Fast Fourier Transform
ICI	Inter carrier Interference
IFFT	Inverse Fast Fourier Transform
ISI	Inter symbol Interference
LAN	Local Area Network
LMMSE	Linear MMSE
LS	Least Square
MMSE	Minimum Mean Square Error
MIMO	Multiple Input Multiple Output
MSE	Mean Square error
NMSE	Normalized Mean Square error
OFDM	Orthogonal frequency division multiplexing
QRD	QR Decomposition
QRD LS	QRD Least square
SLS	Scaled Least Square
WiMAX	Worldwide Interoperability for Microwave Access

Chang [1] proposed the OFDM technique in 1966 with the principle of transmitting messages simultaneously over multiple carriers in a linear band limited channel without ISI and ICI. Earlier form of OFDM included a huge number of oscillators and lucid demodulators. Weinstein and Ebert in 1971 applied DFT to the modulation and demodulation processes [2].

Further, in 1980, Peled and Ruiz introduced the idea of cyclic prefix to sustain frequency orthogonality over the dispersive channel [3]. OFDM is considered as a major technique for wireless multimedia communications beyond 3G. The complexity of a maximum likelihood or a suboptimal equalization used in a frequency selective channel increases exponentially with the product of the bandwidth and delay spread. The OFDM modulation is built with inverse FFT to transform a frequency selective fading channel into orthogonal flat fading channels, thereby, maintaining a constant channel characteristic [4]. MIMO-OFDM systems also converts a frequency selective MIMO channel into multiple flat fading channels [5], but also has the ability to exploit the multipath propagation. The separability of the MIMO channel depends on the existence of rich multipath, which builds the channel to be spatially selective. The maximum spatial diversity attained for a MIMO channel which is non-frequency selective fading type, is proportional to the product of the number of receiving and transmitting antennas [6].

In MIMO-OFDM, high data rates are achieved without the necessity for higher bandwidth, as the parallel channels are formed over the same time and frequency [7, 8]. The higher bandwidth efficiency makes MIMO to be included in the future Broadband Wireless Access (BWA) standard. Hence the MIMO-OFDM has become a smart technique for future high data rate systems [9-11].

2. System Model

Random data input is mapped into symbols with suitable modulation technique following the WiMAX standard. At this phase, the sequences of symbols that are complex valued are obtained by converting the group of binary bits. In WiMAX, the conditions that define the mandatory constellations are QPSK and 16QAM. The 64QAM is a non-compulsory constellation, but it is implemented in some situations like the case of downlink transmission. The loss in signal strength at the receiver end due to signal fading and noise is balanced using space time coding techniques. In grouping with OFDM, the space time block codes give higher performance and the mapped symbols are encoded spatially using STBC [12].

The total bin size is considered as N. To adjust the bin size, null subcarriers are used to represent carriers with zero energy or energy not offered. Assuming N_u as the data subcarriers in every parallel sub channel and N_g as the pilot subcarriers added to it, the total subcarriers takes the form of N (N_{used} + N_{pilot} + N_{null} = N) where N_{null} is the set of null carriers added to adjust the size. Then the IFFT block are fed with symbols one by one, so that the time domain signal transformations take place as specified in Eq. (1).

$$s(m) = \sum_{-\frac{N_{used}}{2}}^{\frac{N_{used}}{2}} S(K) e^{\frac{j2\pi k}{N_{FFT}}}, 0 \leq m \leq \; N-1, \tag{1}$$

where $k \neq 0.$ Here, $s(m)$ stands for nth modulated OFDM symbol. N_{used} denotes the count of subcarriers which are non-suppressed.

The k^{th} modulated subcarrier is represented as,

$$\boldsymbol{S}(mN \; + \; k) = \begin{bmatrix} S_1(mN+k) \\ S_2(mN+k) \\ \vdots \\ \vdots \\ S_{N_t}(mN+k) \end{bmatrix} \tag{2}$$

where $k \neq 0.$ Here, $s(m)$ stands for nth modulated OFDM symbol. N_{used} signifies the count of non-suppressed subcarriers.

The quality of the signal transmitted depends on the process that takes place in the wireless channel. The SUI model is used to define the impulse response of the channel. The procedure followed at the transmitter end is reversed to suit at the receiver side. Figure 1 portrays the entire signal processing method followed in the system model.

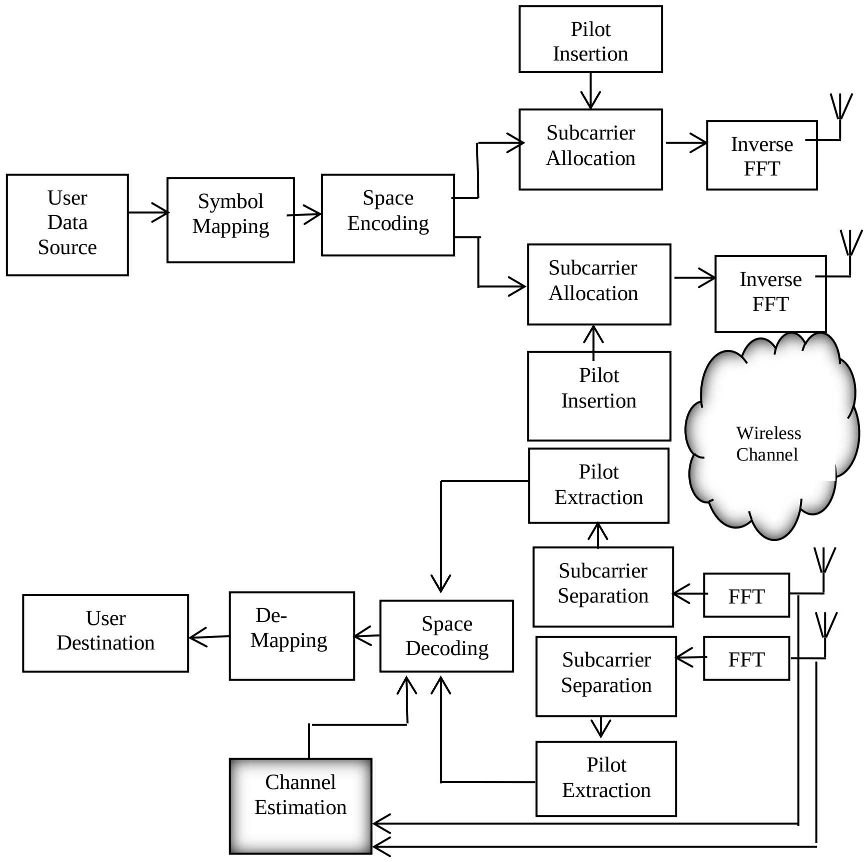


Fig. 1. System model.

The complex baseband equivalent receive signal is

$$\boldsymbol{r}(mN_{tot}+n)=\sum_{l=0}^{L-1} h_{l,m}\boldsymbol{u}(mN_{tot}+n-l)+\boldsymbol{w}(mN_{tot}+n), \tag{3}$$

In the above equation, $u(m)-$cyclic prefix added signal and $\boldsymbol{h}_{l,m}$ is l^{th} matrix-valued CIR coefficient. To combat ISI, the first $N_g N_r$ elements of r(m) are removed completely. The resulting OFDM symbol is $\mathbf{y}(m)$ which is free from ISI. Finally taking FFT on the $\boldsymbol{y}(m)$, we get the frequency domain MIMO-OFDM signal with $\boldsymbol{H}_{m,diag}$ block diagonal matrix as,

$$\boldsymbol{Y}(m)=\boldsymbol{H}_{m,diag}\boldsymbol{S}(m)+\boldsymbol{W}(m) \tag{4}$$

Efficient channel tracking technique is used to estimate pilot sequence. This is employed for estimation of the data subcarriers. The original data is retrieved after decoding and demodulating. The training based estimation algorithm decreases the efficiency of the system but increases the accuracy of the information. The pilot placing method and the number of pilots used decides the efficiency as well as the accuracy of the system. The use of higher number of pilots leads to increase in bandwidth and power requirements and vice versa.

3. Channel Estimation Techniques

The channel information like its amplitude and phase measurement is a very important and mandatory signal processing in a wireless communication to improve the performance of the designed system. Because of this, much research work is going on, in the channel estimation area [13, 14]. More channel estimation approaches have work in co-operation with other techniques like signal detection to further improve the capacity of channel estimation as well as the bit error rate performance of the system. Minimising the computational complexity and making it suitable for a practical implementation is also necessary, in addition with the bit error rate improvement [15, 16]. Reduction in the number of the mathematical computations helps us to reduce the bandwidth and energy requirement.

The channel estimation in a MIMO-OFDM system is a primary and challenging task, as the signals received is a combination of the signals from several transmits antennas. In training based algorithm, pilot sequence is used to estimate the channel, while it is not required in blind estimation technique. In the earlier phase of MIMO-OFDM system usage, pilot allocation methods that convert channel estimation of MIMO-OFDM into the channel estimation of SISO-OFDM were proposed generally. For a given pilot scheme, only one of the transmitter antenna sends its pilot signal at a given subcarrier while the others remain silent [17]. The WiMAX systems also use similar pilot scheme suitable for two antenna situation.

The transform domain methods are successfully applied in MIMO-OFDM systems that are using pilots [18, 19]. A lower bound is defined to eliminate the interference from other antennas. In MIMO-OFDM systems, in addition to the frequency and time domain correlations, the spatial domain correlation can also be explored. The use of spatial domain correlation provides additional gain subjected to the observation, when the correlation is beyond 0.8. With uncorrelated CIR taps, the spatial correlation between the subcarriers having the same indices is the same as between the antenna elements. The utilization of the spatial correlation is also explored through Kalman filtering approach for channel tracing in time domain [20]. The additional benefit of using spatial correlation is that it improves the channel estimate of MIMO systems through pre-filtering in time domain. Here, the time domain LMMSE channel estimation is utilized [21].

3.1. Classical channel estimation algorithms and modified channel estimation algorithm

The Least Square (LS) and Minimum Mean Square Error (MMSE) algorithms belong to classical channel estimation algorithm. The SLS and RMMSE come under modified channel estimation algorithms [22]. The complexity reduced algorithm is analysed finally and selected as an optimal one. The obtained transmitted pilot's inverse is multiplied by the received pilot in simple channel estimating cases. This method is known as LS estimator [23] and the channel estimation based on this technique is represented as,

$$\widehat{\boldsymbol{H}}_{LS} = \boldsymbol{S}^{\dagger}\boldsymbol{Y} \tag{5}$$

$S^{\dagger} = (S^H S)^{-1} S^H$ is the pseudo-inverse of S.

The LS estimator does not require any channel statistics, but they are affected by mean square error in a huge amount. To overcome this limitation, the estimator is scaled, improved and named as scaled LS (SLS) estimator. The SLS estimation of the channel can be expressed as,

$$\widehat{\boldsymbol{H}}_{SLS} = \gamma_o \widehat{\boldsymbol{H}}_{LS} \tag{6}$$

$$= \frac{tr\{\boldsymbol{R_H}\}}{J_{LS} + tr\{\boldsymbol{R_H}\}} \widehat{\boldsymbol{H}}_{LS} = \frac{tr\{\boldsymbol{R_H}\}}{\sigma^2 N_r tr\left\{\left(\boldsymbol{SS}^H\right)^{-1}\right\} + tr\{\boldsymbol{R_H}\}} \boldsymbol{YS}^{\dagger} \tag{7}$$

N_r- the number of receiving antennas; $\boldsymbol{R}_H = E\{H^H H\}$ – channel correlation matrix; Receive noise power$-\sigma^2$; Note that the SLS estimator is a function of the ratio$\left(\frac{tr\{R_H\}}{\sigma^2}\right)$. Therefore, before using the SLS approach, this ratio should be estimated.

To further reduce the MSE, the MMSE estimator makes use of the channel's second order statistics [24]. The primary challenge in designing a robust communication system is to provide a higher capacity system with reduced computational complexity. In MMSE technique [23], power delay profile (PDP) with uniform value is employed to strike a balance between the two. But the computational process complexity for the observed samples is found to increase in an exponential way. To overcome this limitation, linear MMSE (LMMSE) technique is developed, in which the subcarrier of pilot's channel response is measured by LS or LMMSE. This initial information helps in detecting data subcarrier using interpolation method. The LMMSE gives better performance at small SNR compared to that of LS, but at the expense of increase in complexity.

The MMSE channel estimate in the frequency domain is,

$$\boldsymbol{H}_{MMSE} = \boldsymbol{YA} \tag{8}$$

The matrix A is calculated as,

$$\boldsymbol{A} = arg\ \min_{A} E\left\{\|\boldsymbol{H} - \boldsymbol{YA}\|^2{}_F\right\} \tag{9}$$

The optimal value of A can be obtained from $\partial\varepsilon/\partial A = 0$ and is expressed by

$$\boldsymbol{A} = (\boldsymbol{S}^H \boldsymbol{R_H} \boldsymbol{S} + \sigma^2 N_r \boldsymbol{I})^{-\mathbf{1}} \boldsymbol{S}^H \boldsymbol{R_H} \tag{10}$$

Hence, the linear MMSE estimator can be represented as

$$\widehat{\boldsymbol{H}}_{MMSE} = \boldsymbol{Y}(\boldsymbol{S}^H \boldsymbol{R_H} \boldsymbol{S} + \sigma^2 N_r \boldsymbol{I})^{-\mathbf{1}} \boldsymbol{S}^H \boldsymbol{R_H} \tag{11}$$

In the above expression, $\boldsymbol{R_H}$ indicates the covariance matrix of the channel with a variance of σ^2. If the noise is to be ignored, set σ^2=0. In this case, both LS and MMSE estimators become one and the same. The need of covariance matrix of the channel in both the time and frequency domains is the major disadvantage of the LMMSE estimation.

At the receiver end the channels covariance matrix is unknown. It has to be predicted based on the previous information on channel estimates. But, it is difficult to track the channel covariance matrix due to sudden changes in the channel characteristics in applications such as mobile communication. For example, it is possible to know the restraints on the covariance matrix of a real channel only when the maximum delay of the channel and Doppler spread data are known. In traditional LMMSE algorithm, it is required to know full channel covariance information. Later on, the modified LMMSE algorithm is developed with improved performance in which only fractional information on covariance matrix is needed. In relaxed MMSE algorithm (RMMSE), which is an improved version of the linear MMSE, only small amount of channel correlation matrix at the receiver end is sufficient [3].

The MMSE requires perfect knowledge of the correlation matrix assumption. This assumption is not reachable in practical situations. It can be alternatively written as $\alpha\mathrm{I}$ in lieu of $\mathrm{R_H}$. To minimize the error, the parameter α can be adjusted.

Replacing $\boldsymbol{R_H}$ with $\alpha\boldsymbol{I}$ and applying the matrix inversion lemma, we can rewrite this equation as,

$$\widehat{\mathbf{H}} = \alpha\mathbf{Y}(\alpha\mathbf{S}^{\mathrm{H}}\mathbf{S} + \sigma^2\mathrm{N_r}\mathbf{I})^{-\mathbf{1}}\mathbf{S}^{\mathrm{H}} \quad (12)$$

By assuming orthogonal training, the channel MSE can be computed as

$$\mathcal{J}_{\mathrm{RMMSE}} = \left(\mathrm{E}\left\{\left\|\mathbf{H} - \widehat{\mathbf{H}}\right\|^2{}_{\mathrm{F}}\right\}\right).$$

MSE can be minimized by substituting optimum value of α. for any training matrix, the RMMSE channel estimator is given by

$$\mathbf{H}_{\mathrm{RMMSE}} = \mathbf{Y}\left(\mathbf{S}^{\mathrm{H}}\mathbf{S} + \frac{\sigma^2\mathrm{N_r}\mathrm{N_t}}{\mathrm{tr}\{\mathbf{R_H}\}}\mathbf{I}\right)^{-\mathbf{1}}\mathbf{S}^{\mathrm{H}} \quad (13)$$

$\mathrm{tr}\{\mathrm{R_H}\}$ is assumed to be known or estimated.

The RMMSE algorithm estimation error is given by,

$$\mathcal{J}_{\mathrm{RMMSE}} = \frac{\mathrm{tr}\{\mathbf{R_H}\}\sigma^2\mathrm{N_r}\mathrm{N_t}^2}{\mathrm{tr}\{\mathbf{R_H}\}\mathrm{tr}\{\mathbf{S}^{\mathrm{H}}\mathbf{S}\}+\sigma^2\mathrm{N_r}\mathrm{N_t}^2} \quad (14)$$

and

$$\frac{\mathcal{J}_{\mathrm{RMMSE}}}{\mathcal{J}_{\mathrm{LS}}} = \frac{\mathrm{tr}\{\mathbf{R_H}\}\mathrm{tr}\{\mathbf{S}^{\mathrm{H}}\mathbf{S}\}}{\mathrm{tr}\{\mathbf{R_H}\}\mathrm{tr}\{\mathbf{S}^{\mathrm{H}}\mathbf{S}\}+\sigma^2\mathrm{N_r}\mathrm{N_t}^2} \quad (15)$$

If $\sigma^2 > 0$, then $\mathcal{J}_{RMMSE} < \mathcal{J}_{LS}$ and hence the relaxed MMSE channel estimation method operates always greater than the LS estimator. The enhancement of the RMMSE estimator over the LS estimator is notably prominent if the SNR is low. The above cited papers considered AWGN, Rayleigh and WLAN channels. In this research, all this algorithms have been applied in WiMAX scenario and tested over SUI channel model. Different fading conditions have been analysed.

3.2. Decomposition in channel estimation

In wireless communications, MIMO and OFDM are recognized as one of the most important breakthroughs in advanced communications [25].But in practical applications, apart from the goals, targets and achievements, still there is a gap with the theoretical bound [26]. Availability of imperfect channel information and growing mathematical computational complexity are the major reasons for this. In this section, complexity reduced channel tracking algorithm will be discussed.

The computation of the LS solution is a complex phenomenon, as it involves matrix inversion. This is unfavourable for hardware implementation. The schemes that avoid explicit inversions include Cholesky, SVD, QR decomposition (QRD) and lower upper. They are robust and more appropriate for hardware implementation and also help to reduce the computational complexity of the system. The QR decomposition uses an orthogonal matrix triangularization technique to reduce a full rank matrix into a simpler form. When QR method is preferred for channel tracking, the decomposition has to be performed every time when a new channel estimate is available.

Bai and Yuan [27] combined the good features of the decomposition and the required features of the lattice structure to form QRD-LSL algorithm and proved that it can be extended to linear interpolation from linear prediction. Jenq-Tay Yuan [28] further extended the QRD-LSL algorithm from filtering to smoothening without compromising the computational cost. The QR decomposition algorithm is most preferred in modern MIMO-OFDM systems for data detection [29, 30]. After the channel response is QR decomposed, the procedure for signal processing gets simplified and the data can be kept in orthogonal form. After decomposition, the channel response is transformed to an upper triangular matrix, thereby reducing the interference in every received signal. The complexity of the equalizer is decreased and therefore the total size will not be increased due to the decomposition process.

The different techniques used to compute QR decomposition are Gram-Schmidt orthonormalization method, Givens rotations method and the Householder reflections. In QRD method, the complexity is found to increase linearly with the number of transmit antennas of the system compared to the exponential increase in the case of LS method. Therefore, QRD method is preferred where more transmit antennas are used, as it will not explode in complexity like the LS method [31]. The major goal in developing the communication systems is to choose more suitable channel estimation technique that can be made adaptive to the environment. The adaptation can be done by using information from other physical layer blocks too. For example, the information available at blocks such as frequency offset estimation, timing offset estimation and the output of the decoder can all be used to determine the most appropriate channel estimation technique.

QR decomposition is an alternative method for determining matrix inversion required in LS. Let us define the received signal in frequency domain as, $\boldsymbol{Y} = \boldsymbol{HS} + \boldsymbol{W},$ with W -noise parameter. It can be redefined with Fourier matrix F as, $\boldsymbol{Y} = \boldsymbol{XFh} + \boldsymbol{W} = \boldsymbol{Vh} + \boldsymbol{W}.$

The following steps present the QRD algorithm to find solution for LS problem:

1. The initial step is to represent the LS error function, $\varepsilon = \boldsymbol{Y} - \mathrm{V}\tilde{\mathrm{h}}$.
2. The V matrix is decomposed into upper triangular matrix R and Hermitian matrix Q using Householder algorithm as,

$$\boldsymbol{Y} = \boldsymbol{V}\widetilde{\boldsymbol{h}} = \boldsymbol{Q}_{N_t \times N_t} \begin{bmatrix} \boldsymbol{R} \\ 0 \end{bmatrix}_{N_t \times N_r} \widetilde{\boldsymbol{h}}$$

3. Hermitian of Q has to be multiplied on both sides of the equation yields,

$$\begin{bmatrix} \boldsymbol{R} \\ 0 \end{bmatrix}_{N_t \times N_r} \widetilde{\boldsymbol{h}} = \boldsymbol{Q}_{N_t \times N_t}{}^{H} \boldsymbol{Y}$$

4. Finally, the solution for the channel is obtained using back substitution

In this work, Householder is chosen other than the Gram- Schmidt because of its stability over Gram-Schmidt algorithm.

Using Householder algorithms, the transmission matrix $\boldsymbol{S}_{N_t \times N_r}$ can be processed as follows.

1. Take a column of matrix V for example X_1 and calculate$\|\boldsymbol{\mathcal{X}}\| = |\alpha|$.

2. Then, the expressions for U, P, Q, Q_1 are computed as ,

$$U = X - \alpha e1$$
$$P = \frac{U}{\|U\|}$$
$$Q = I - 2PP^T$$
$$Q_1 V = \begin{bmatrix} \alpha_1 & * & \cdots & * \\ 0 & & & \\ \vdots & & \hat{V} & \\ 0 & & & \end{bmatrix}$$

This procedure has to be repeated again for $\hat{V}$, Resulting in a Householder matrix Q_2'. This procedure can be used continuously to transform a $N_t \times N_r$ matrix in to upper triangular matrix.

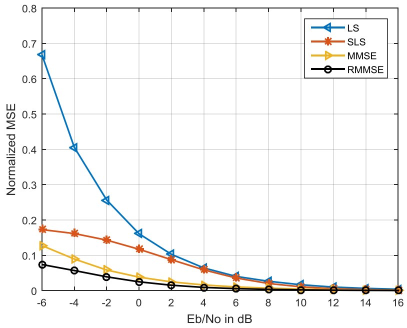
4. Simulation Study and Discussion

The system model is simulated using Matlab taking the standard SUI channel model parameters along with system parameters mentioned in Table 1for different fading conditions. The performance of various channel estimation algorithm like LS, SLS, MMSE, and RMMSE, QRD-LS and QRD-MMSE are analysed and compared. Results are tested in two different terrains with high fading and low level fading scenario.

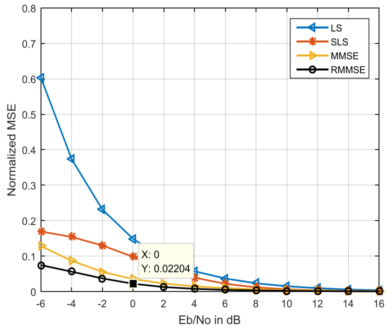
Table 1. MIMO OFDM system parameters.

	Specification
Number of Transmitting, Receiving antennas	2×2
Number of OFDM subchannels	1024
Number of transmitted OFDM frames	1024
Space Encoding	STBC
Symbol Mapping	BPSK

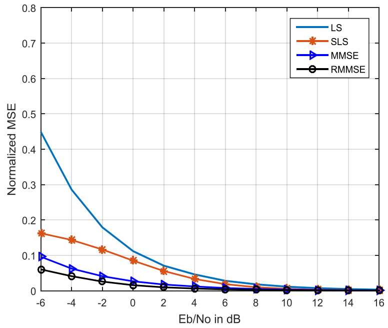
Figure 2 shows the normalized mean square error of all the classical channel estimators measured under SUI-1 channel for various value of correlation factor k from zero to one [32]. It is verified that the RMMSE algorithm is superior to other mentioned algorithms.



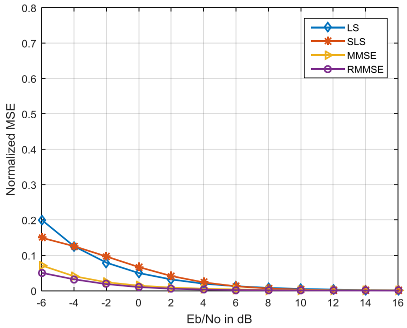
(a) Correlation factor=0.



(b) Correlation factor=0.2.



(c) Correlation factor=0.4.

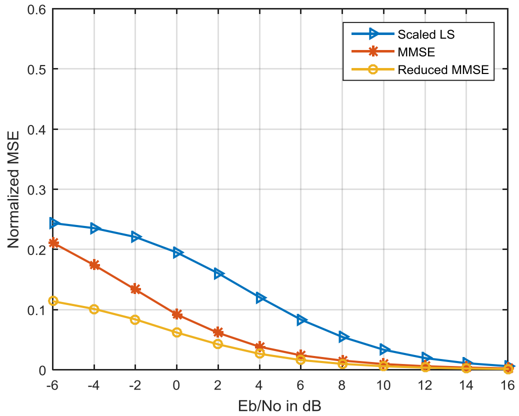


(d) Correlation factor=0.7.

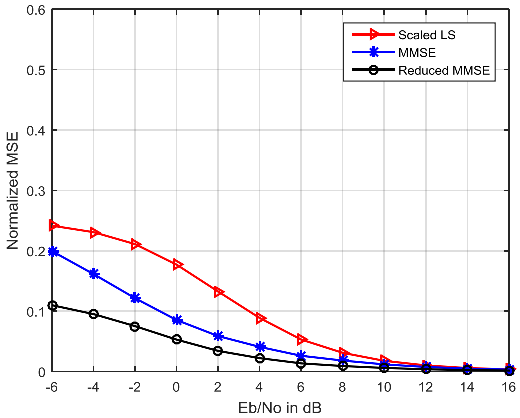
Fig. 2. SUI-1Channel estimation at different values of correlation factor.

It is observed that the LS algorithm is the least preferred one compared to all other algorithms discussed in the model. The scaling factor introduced in the scaled linear estimator helps to reduce the normalized error and it is verified in the above results. The MMSE algorithm is found to perform better than the LS and SLS estimators. But the MMSE requires channel information to be provided well in advance. In a highly correlated channel, the MMSE performance decreases with the usage of orthogonal probing. However, when the number of antenna at the transmitter end is large as well as with low SNR this effect becomes more prominent. From the above Matlab simulation, it is observed that, estimator error performance improves with the increment in the correlation factor value as discussed in the theory and it is tested with low traffic condition. If RMMSE has been considered for analysis, NMSE is reduced from 0.0898 to 0.0506 at -6dB when correlation factor is 0, 0.7 respectively.

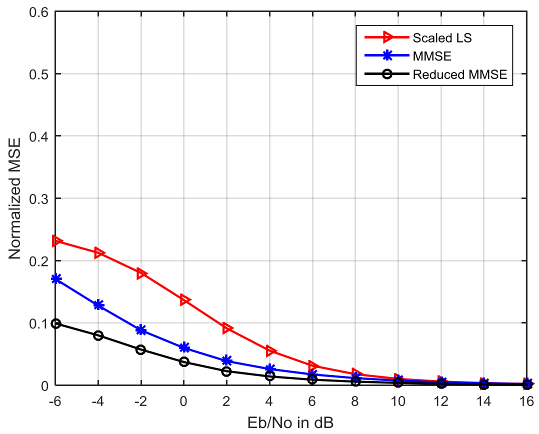
The estimator's efficiency is measured in terms of NMSE metric with heavy to moderate traffic condition and it is shown in the following Fig. 3. As it is observed that the LS estimators are not efficient at low bit energy level, it is not included in the remaining process.



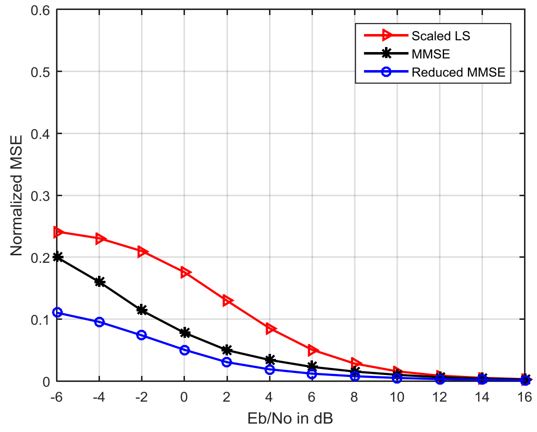
(a) Correlation factor=0.



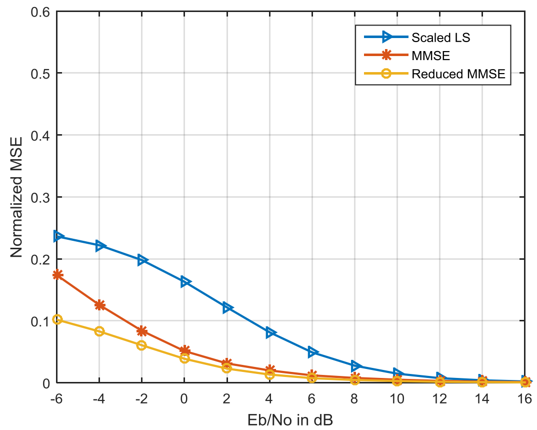
(b) Correlation factor=0.2.



(c) Correlation factor=0.4.



(d) Correlation factor=0.7.

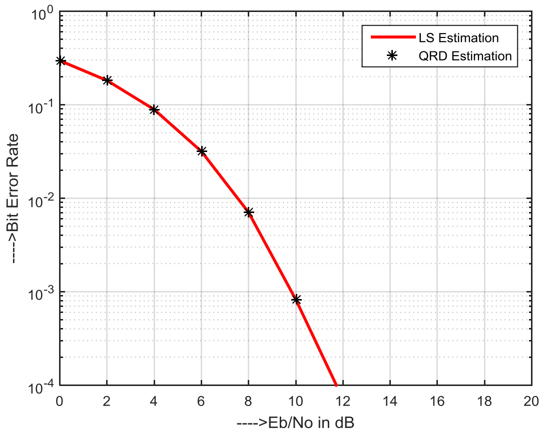


(e) Correlation factor=1.

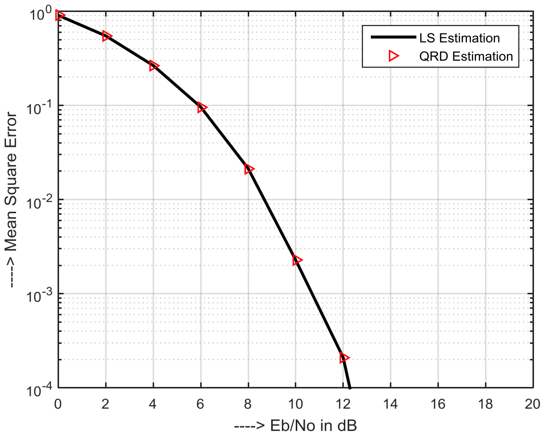
Fig. 3. SUI-6 Channel estimation at different values of correlation factor.

It is observed that, in heavy traffic scenario also, reduced MMSE estimator performs better than all other estimators. From the above Matlab simulation, it is observed that, estimator error performance improves with the increment in the correlation factor value in moderate to heavy traffic condition fading scenario too. From the above results, it has been verified that the RMMSE outperforms the other mentioned algorithms at low signal to noise ratio in all traffic conditions. But the complexity in terms of number of multiplications, divisions and additions are higher in these algorithms. So it leads to the requirement of complexity reduced technique in signal detection.

System with multicarrier transmission (OFDM) is simulated with 1024 subcarriers and the number of taps =3 in Matlab under Rayleigh fading environment. BER and MSE are measured for various values of E_b/N_o and it is shown in in Fig. 4.



(a) BER performance.



(b) MSE performance.

Fig. 4. LS and decomposed LS algorithm performance in OFDM

QR decomposition algorithm is simulated on Space time coded MIMO with simultaneous MFSK system and the performance is compared with LS in terms of number of erroneous bit per transmitted sequence and it is represented in Fig. 5.

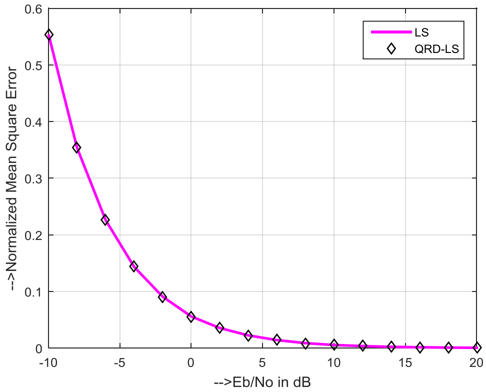


Fig. 5. LS and decomposed LS algorithm performance in MIMO OFDM.

It is observed that, in both systems, LS and QR applied LS gives the same performance in both OFDM and MIMO OFDM. The primary aim of using QR decomposition is to lessen the complexity of computation of the LS channel estimation. The computational complexity in terms of number of mathematical operations has been measured and the result is given in the following figures for various values of channel taps and Transmitting antennas.

Figure 6 shows the result when the transmitter antenna elements increased from 1 to 6. Since the size of the channel matrix increases, the number of operations involved in both algorithms also increases. But lesser number of computations is involved in QRD than LS. Also, the complexity increases with the number of array element at the transmitter is linear in nature in QRD but is in exponential in case of LS algorithm.

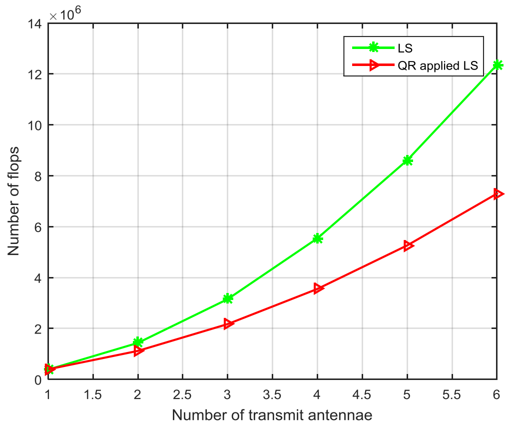


Fig. 6. Complexity of LS and QRD-LS for various number of transmitting antennae.

Figure 7 shows the complexity comparison when the number of channel length is varied for a given number of transmitted antennas. Since the amount of strange parameters to be calculated increases, when larger length channel is included, the flops involved increases in both algorithms. But, in this scenario also, QRD gives better performance than LS as usual.

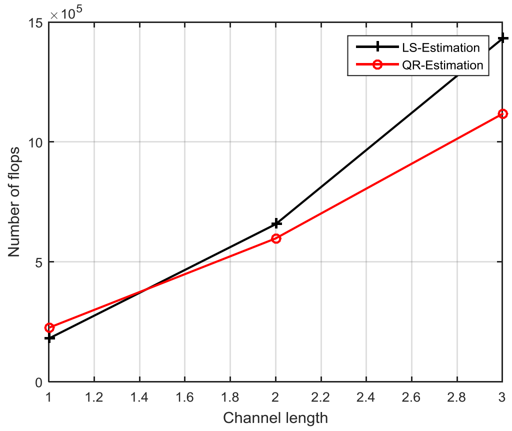


Fig. 7. Complexity vs channel taps in LS and QRD-LS.

The complexity equations are derived by counting each type of operations in the various algorithms by considering N number of subcarriers and L-channel length $(M = L \times N_t)$. The total number of mathematical operations involved in LS and decomposed LS with two transmitting antennas and three taps are summarized in Table 2. The Worldwide Interoperability for Microwave Access (WiMAX) is a promising wireless technology which delivers data at high rates covering larger area. To retrieve desired signals in such technology, we need to incorporate appropriate Channel estimation and signal detection techniques at the receiver. In this paper, efficient QR based channel estimation has been proposed. Further improvement in system efficiency in terms of reduction in bit error rate is possible with the inclusion of optimum signal detection technique at the receiver [33].

Table 2. Complexity comparisons of LS and QRD channel estimation techniques.

Technique	LS		QRD	
	Order	Total	Order	Total
Number of Multiplications	NM	80088	$\mathrm{M}^2/2 - \mathrm{M}/2$	61346
Number of Additions / Subtractions	NM − M	73902	$\mathrm{M}^2/2 + \mathrm{M}/2 - 1$	58256
Number of Divisions	0	57	0	18
Number of Square Roots	0	0	0	12
Simulation Time in Sec.		0.0013		0.0017

5. Conclusions

A number of training-based MIMO channel estimation methods and their performance are investigated. The prevalent LS, MMSE schemes are measured along with a novel SLS and relaxed MMSE techniques. The SLS and RMMSE techniques are found to give better performance than the other two schemes. The different kind of training matrices are analysed and optimal selection is made and applied. For each of the considered techniques, performances are measured and compared in terms of normalized mean square error. The LS algorithm technique shows the least performance compared to SLS, MMSE and RMMSE. The MMSE performance decreases when the channel is highly correlated. The functioning of the estimator is observed to improve with the increase in correlation. The system is simulated in Matlab with SUI-1 and SUI-5 Channel model for various combinations of transmitting and receiving antennae and for different correlation values. From the simulation results, the RMMSE estimation is found to perform better in all situations.

- In SUI-6 channel, normalized mean square error of 0.1 is achieved at -6dB. Because of lower level of fading in SUI-1 channel, it takes less than -6dB to achieve the same error level.
- In a decomposed algorithm, computational complexity reduction has been achieved up to 81.64% with lesser number of channel lengths and it reaches up to 63.68% with the length increased to 6 than other algorithms which are not decomposed. Reduction in the number of mathematical operations leads to less energy requirement in data transmission system.

References

1. Chang, R.W. (1966). Synthesis of band-limited orthogonal signals for multichannel data transmission. *Bell System Technical Journal*, 45(10), 1775-1796.
2. Weinstein, S.; and Ebert, P. (1971). Data transmission by frequency-division multiplexing using the discrete Fourier transform. *IEEE transactions on communication technology*, 19(5), 628-634.
3. Andrews, J.G.; Ghosh, A.; and Muhamed, R. (2007). *Fundamentals of WiMAX: understanding broadband wireless networking*. Pearson Education.
4. Cho, Y.S.; Kim, J.; Yang, W.Y.; and Kang, C.G. (2010). *MIMO-OFDM wireless communications with MATLAB*. John Wiley & Sons.
5. Armstrong, J. (2002). Peak-to-average power reduction for OFDM by repeated clipping and frequency domain filtering. *Electronics Letters*, 38(5), 246-247.
6. Bharghavan, V.; Demers, A.; Shenker, S.; and Zhang, L. (1994). MACAW: a media access protocol for wireless LAN's. *ACM SIGCOMM Computer Communication Review*, 24(4), 212-225.
7. Wolniansky, P. W.; Foschini, G. J.; Golden, G.D.; and Valenzuela, R. A. (1998). V-BLAST: An architecture for realizing very high data rates over the rich-scattering wireless channel. *In URSI International Symposium on Signals, Systems, and Electronics,* 295-300.

8. Golden, G.D.; Foschini, C.J.; Valenzuela, R.; and Wolniansky, P.W. (1999). Detection algorithm and initial laboratory results using V-BLAST space-time communication architecture. *Electronics letters*, 35(1), 14-16.
9. Sartori, P.J.; Baum, K.L.; and Vook, F.W. (2002). Impact of spatial correlation on the spectral efficiency of wireless OFDM systems using multiple antenna techniques. *In IEEE 55th Vehicular Technology Conference Proceedings,* 3(1), 1150-1154.
10. Foschini, G.J.; and Gans, M.J. (1998). On limits of wireless communications in a fading environment when using multiple antennas. *Wireless Personal Communications*, 6(3), 311-335.
11. Cimini, L. (1985). Analysis and simulation of a digital mobile channel using orthogonal frequency division multiplexing. *IEEE Transactions on Communications*, 33(7), 665-675.
12. Costa, N.; and Haykin, S. (2010). *Multiple-input multiple-output channel models: Theory and practice,* John Wiley & Sons.
13. Bagadi, K.P.; and Das, S. (2010). MIMO-OFDM channel estimation using pilot carries. *International Journal of Computer Applications*, 2(3), 1-8.
14. Kavitha, K.V.N.; Saravanan, K.; Ghosh, S.; and Khara, S. (2013). Effective channel estimation technique with adaptive modulation for MIMO-OFDM system. *Journal of Theoretical and Applied Information Technology*, 54(2), 313-319.
15. Savaux, V.; and Louët, Y. (2016). LMMSE channel estimation in OFDM context: a review. *IET Signal Processing,* 11(2), 123-134.
16. Hajjaj, M.; Chainbi, W.; and Bouallegue, R. (2016). Low-rank channel estimation for MIMO MB-OFDM UWB system over spatially correlated channel. *IEEE Wireless Communications Letters*, 5(1), 48 - 51.
17. Ozdemir, M.K.; and Arslan, H. (2007). Channel estimation for wireless OFDM systems. *IEEE Surveys and Tutorials*, 9(2), 18-48.
18. Dowler, A.; Doufexi, A.; and Nix, A. (2002). Performance evaluation of channel estimation techniques for a mobile fourth generation wide area OFDM system. *In IEEE 56th Conference on Vehicular Technology Proceedings,* 4(1), 2036-2040.
19. Zhao, Y.; Li, W.; and Wu, W. (2001). An efficient channel estimation method for OFDM systems with multiple transmit antennas. *In Proceedings of International Conference on Info-tech and Info-net,* 2(1), 335-339.
20. Roman, T.; Enescu, M.; and Koivunen, V. (2003). Recursive estimation of time-varying channel and frequency offset in MIMO OFDM systems. In *14th IEEE Proceedings on Personal, Indoor and Mobile Radio Communications,* 2(1), 1934-1938.
21. Kiessling, M.; Speidel, J.; Viering, I.; and Reinhardt, M. (2003). Statistical prefiltering for MMSE and ML receivers with correlated MIMO channels. *In Wireless Communications and Networking,* 2(1), 919-924.
22. Biguesh, M.; and Gershman, A.B. (2006). Training-based MIMO channel estimation: a study of estimator tradeoffs and optimal training signals. *IEEE transactions on signal processing*, 54(3), 884-893.

23. Vaughan-Nichols, S.J. (2004). Achieving wireless broadband with WiMax. *IEEE Computer*, 37(6), 10-13.
24. Simon, E.P.; Ros, L.; Hijazi, H.; Fang, J.; Gaillot, D.P.; and Berbineau, M. (2011). Joint carrier frequency offset and fast time-varying channel estimation for MIMO-OFDM systems. *IEEE Transactions on Vehicular Technology*, 60(3), 955-965.
25. Hanzo, L.; El-Hajjar, M.; and Alamri, O. (2011). Near-capacity wireless transceivers and cooperative communications in the MIMO era: Evolution of standards, waveform design, and future perspectives. *Proceedings of the IEEE*, 99(8), 1343-1385.
26. Hanzo, L.; Haas, H.; Imre, S.; O'Brien, D.; Rupp, M.; and Gyongyosi, L. (2012). Wireless myths, realities, and futures: from 3G/4G to optical and quantum wireless. *Proceedings of the IEEE*, 100(1). 1853-1888.
27. Bai, Y.-W.; and Yuan, J.T. (1998). QRD-based LSL interpolators. II. A QRD-based LSL interpolation algorithm. *Proceedings of the 1998 IEEE International Conference on Acoustics, Speech and Signal Processing*, 3(1), 1473-1476.
28. Yuan, J.T. (1999). A modified QRD for smoothing and a QRD-LSL smoothing algorithm. *IEEE transactions on signal processing*, 47(5), 1414-1420.
29. Xining, X.; Xinglin, W.; Minqiang, T.; Feng, Z.; and Zhiqiang, H. (2012). Mapping QR decomposition algorithm for MIMO detection. In *7th International ICST Conference on Communications and Networking*,315-320.
30. Peng, R.; Teo, K. H.; Zhang, J.; and Chen, R.R. (2008). Low-complexity hybrid QRD-MCMC MIMO detection. *Proceeding of IEEE Global Telecommunications Conference*, 1-5.
31. Abdolee, R. (2006). *Performance of MIMO Space-Time coded System and Training based channel estimation for MIMO-OFDM System.* Ph.D. Thesis. Universiti Teknologi, Malaysia.
32. Kavitha, K.V.N.; and Bagadi, K.P. (2016).Slope intercept model estimation for MIMO–OFDM system in the WiMAX environment. *WSEAS Transactions on Communications,* 15(1),224-232.
33. Kavitha, K.V.N.; and Bagadi, K.P. (2017). Efficient channel estimation and signal detection schemes for multiple input and multiple output system under WiMax environment. *International Journal of Intelligent Engineering & Systems*, 10(5), 48-56.