Synchronization and Channel Estimation in OFDM

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Abstract - In this paper, we first compare least square (LS) and linear minimum mean square error (LMMSE) channel estimation method with frequency and time domain in orthogonal frequency division multiplexing (OFDM) systems. We proposed an iterative LMMSE channel estimation in time domain which needn't a priori knowledge for the channel. Simulation results demonstrate that the time domain methods improve the channel estimation performance compare to the frequency domain methods. Moreover, simulation results show that the proposed method has an approximate performance with the conventional LMMSE method.

Keywords: *Timing domain, Frequency domain, Channel estimation OFDM.*

I. INTRODUCTION

Orthogonal frequency-division multiplexing (OFDM) systems have recently gained increased interest. OFDM is used in the European digital broadcast radio system and is being investigated for other wireless applications such as digital broadcast television and mobile communication systems, as well as for broadband digital communication on existing copper networks. We address two problems in the design of OFDM receivers. One problem is the unknown OFDM symbol arrival time. Sensitivity to a time offset is higher in multicarrier systems than in single-carrier systems. A second problem is the mismatch of the oscillators in the transmitter and receiver. The demodulation of a signal with an offset in the carrier frequency can cause a high bit error rate and may degrade the performance of a symbol synchronizer. A symbol clock and a frequency offset estimate may be generated at the receiver with the aid of pilot symbols known to the receiver by maximizing the average log-likelihood function. Redundancy in the transmitted OFDM signal also offers the opportunity for synchronization. We present and evaluate the joint maximum likelihood (ML) estimation of the time and carrier-frequency offset in OFDM systems. The key element that will rule the discussion is that the OFDM data symbols ahead contain sufficient information to perform synchronization. Our novel algorithm exploits the cache prefix preceding the OFDM symbols, thus reducing the need for pilots.

The OFDM system model

Discrete-time OFDM system model we investigate. The complex data symbols are modulated by means of an inverse discrete Fourier transform (IDFT) on N parallel subcarriers. The resulting OFDM symbol is serially transmitted over a discrete-time channel, whose impulse response we assume is shorter than L samples. At the receiver, the data are retrieved by means of a discrete Fourier transform (DFT) An accepted means of avoiding inter symbol interference (ISI) and preserving orthogonality between subcarriers is to copy the last L samples of the body of the OFDM symbol (N samples long) and append them as a preamble — the cyclic prefix — to form the complete OFDM symbol. The effective length of the OFDM symbol as transmitted is this cyclic prefix plus the body (L + N samples long). The insertion of a cychc prefix can be shown to result in an equivalent parallel orthogonal channel structure that allows for simple channel estimation and equalization. In spite of the loss of transmission power and bandwidth associated with the cyclic prefix, these properties generally motivate its use. In the following analysis we assume that the channel is nondispersive and that the transmitted signal s(k) is only affected by complex additive white Gaussian noise (AWGN) n(k). We will, however, evaluate our estimator's performance for both the AWGN channel and a time-dispersive channel. Consider two uncertainties in the receiver of this OFDM symbol: the uncertainty in the arrival time of the OFDM symbol (such ambiguity gives rise to a rotation of the data symbols) and the uncertainty in carrier frequency (a difference in the local oscillators in the transmitter and receiver gives rise to a shift of all the subcarriers). The first uncertainty is modelled as a delay in the channel impulse response 5(k — 6), where 9 is the integer-valued unknown arrival time of a symbol. The latter is modelled as a complex multiplicative distortion of the received data in the time domain e i2mk, N', where e denotes the difference in the transmitter and receiver oscillators as a fraction of the inter-carrier spacing (1/N in normahzed frequency). Notice that all subcarriers experience the same shift e. These two uncertainties and the AWGN thus yield the received signal.

Synchronization and channel estimation are basic components of communication systems. Synchronization includes timing and frequency synchronization. Morelli analyses some joint synchronization in time domain. The classical synchronization method is proposed by

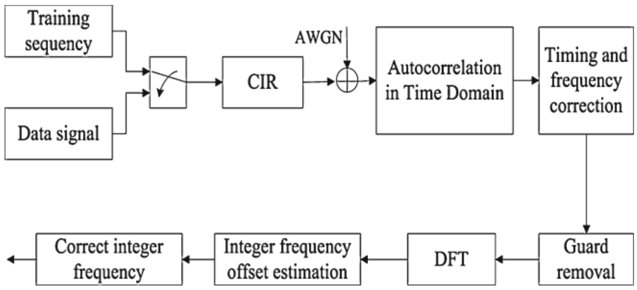

Fig. 1 Synchronization scheme of S&C method

Schmidl and Cox (S&C).The synchronization scheme of S&C method is described in Fig. 1.

S&C proposed a training symbol design with two identical halves in the time domain. The timing offset estimation is achieved by θˆ = max {M(d)}, which means that the timing offset can be estimated by finding the maximum point of the timing metric M(d). M(d) is equal to The frequency offset can be divided into two parts: $\hat{\varepsilon} = \hat{\varepsilon}i + \hat{\varepsilon}f.\hat{\varepsilon}i$ is the integer frequency offset, and εˆ f is the fractional frequency offset which can achieved by εˆ f = φˆ π . φˆ can be achieved by φˆ = angel (P(dˆ)) = P(dˆ). S&C method is one of the popular synchronization methods. However, there are some shortcomings in the S&C method: 1. the timing metric of the S&C algorithm exhibits a large plateau that may greatly reduce the estimation accuracy; 2. the timing synchronization method estimates the strongest path instead of first path. In order to get steeper timing metric. Although the methods proposed by can get steep timing metric than other methods with four specially designed segments, they estimate the strongest path substituted for the first path as the start position. If the first path is not the strongest path in the channel, the timing estimation will introduce inter-symbol-interference (ISI).

Channel estimation has also drawn much interest for efficiently improving the performance of OFDM system. The least square (LS), the minimum mean-square error (MMSE) and the linear minimum mean-square error (LMMSE) estimators. Although the MMSE and the LMMSE estimators have good performance, the LS estimator has an advantage of low complexity for implement in OFDM systems. The LS channel estimator is usually designed in frequency domain to achieve lower complexity than that in time domain, but its performance is worse at noise environment. The symbol period in OFDM systems usually is longer than the duration of the CIR. Since most power of the estimated CIR from LS done in frequency domain is concentrated on a few samples, researchers propose a new channel estimation scheme named as the discrete Fourier transform (DFT)-based estimation shown in Fig. 2. The DFT-based estimation draw large interest because it has the lower computational complexity compared with LS method done in time domain, and can improve the performance of the LS method done in frequency domain.

In this paper, we propose the joint synchronization and channel estimation scheme employing chirp signals as an OFDM training symbol in the multipath channels and block diagram shows in figure 2. In the algorithm, the coarse timing offset is detected by searching for the peak of the correlation and the fractional

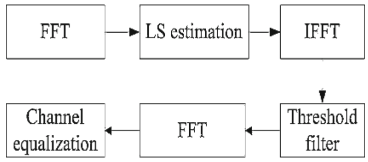

Fig. 2 DFT-based channel estimation

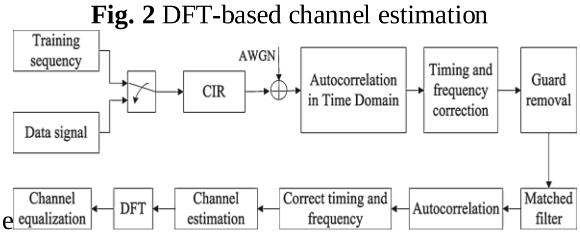

Fig. 3 Block diagram of the system

Frequency offset is extracted from the phase of the highest peak out of the correlation. The integer frequency offset, fine timing offset and channel estimation are estimated based on the characteristics of the chirp signals. The main contributions of the paper are: 1. the more robust ability to find the actual first path instead of the strongest path on the assumption of repeated chirp waveforms in the timing synchronization approach; 2. the accuracy timing estimation can be achieved with the integer frequency estimation, it means that the accuracy timing estimation will not increase the computational complexity to the synchronization scheme; 3. the channel estimation approach can further reduce the computational complexity compared with DFT-based channel estimation method, while achieve the same performance as it.

II. LITERATURE SURVEY

Lin et al. [1] had proposed aim proved orthogonal frequency division multiplexing/offset quadrature amplitude modulation (OFDM/OQAM) strategy for visible light communications (VLC). The OFDM/OQAM VLC system had efficiently enhanced the data rate, and resisted multipath induced ISI and inters carrier interference. Deng and Kavehrad [2], had demonstrated a software defined real-time multiple input multiple output (MIMO) visible light communication system utilizing Single Carrier Quadrature Amplitude Modulation. The system employed two self-sufficient phosphorescent white LED transmitters with 10 MHz bandwidth in the lack of blue filters, and two independent 150 MHz P-I-N photodiode optical receivers. The parameters measured and compared the constellation diagram, error vector magnitude (EVM) and bit error rate

(BER) performance for single-carried M-QAM MIMO VLC employing spatial multiplexing and diversity.

Zhang et al. [3], presented an enhanced strategy to improve the bit error rate (BER) for indoor visible light communication systems. The proposed strategy employed cascaded codes-based channel code and least square discrete Fourier transform (LS-DFT)-based channel prediction to improve the robustness of indoor optical wireless communication channel. The simulation results presented that a 3–5 dB signal noise rate (SNR) gain can be obtained when the BER is 10−3 below the forward error correction (FEC) limit for a 16-quadrature amplitude modulation (QAM).

Chen and Jiang et al [4], presented a new channel estimation (CE) algorithm for indoor downlink (DL) VLC systems, termed to as the adaptive statistical Bayesian minimum mean square error channel estimation (AS-BMMSE-CE). Varing statistic window (VSW) mechanism was developed for exploiting past channel information within a window of adaptively optimized size, such that the channel estimation performance can be significantly boosted. Thorough theoretical analysis was given and verified by extensive numerical results, demonstrating the superior performance of the proposed AS-BMMSE-CE scheme.

Damen et al. [5], considered multiple-input multiple output (MIMO) visible light communication (VLC) systems. The physical layer of VLC system formed upon optical orthogonal frequency division multiplexing (OOFDM). Repetition code (RC), spatial multiplexing (SMUX) and spatial modulation (SMUD) were used as MIMO techniques. As the study of compressive sensing (CS) is becoming a research hotspot, a new perspective for channel estimation is to take advantage of the channel sparsity. F Yang, Dia et al [6]–[7] utilized CS theory to perform the channel estimation in SISO systems. Although the time and frequency training are considered in these literatures, the process can only be performed under time-invariant channel for SISO systems. Doubly selective channel estimation problems in MIMO systems cannot be solved directly using these methods.

R. Mohammadian et al [8] For multiple antenna approaches, multiple input single output (MISO) channel estimation scheme based on the non-orthogonal pilots in frequency domain is investigated. Both the pilots location and power were designed by minimizing the coherence of the associated Fourier submatrix. Two different relaxations were proposed to solve the non-convex problem, which was the first fully deterministic pilot design in a MISO/multi-user scenario with shared pilot subcarriers.

S. Liu et al [9] considered the MIMO-OFDM channel estimation problem, which extended the framework of CS to the structured CS (SCS). The spatial correlation among different transmit antennas are used, which indicates a set of common nonzero support in the SCS framework. Nevertheless, only frequency selective channel is addressed. Kalakech, et al [10], the doubly selective channel estimation was performed using the SCS model, while a differential simultaneous orthogonal matching pursuit (DSOMP) algorithm and structured distributed compressive sensing (SDCS) were further proposed. Q. Qin, L. Gui, et al [11] A channel estimation scheme within multiple symbols was provided. However, the pilot pattern and the frame structure were not fully studied in these schemes which can be further optimized.

S. Pejoski and V. Kafedziski, et al [12] utilized the atomic norm minimization to perform doubly selective channel estimation in SISO systems, while O. E. Barbu, C. N. Manchn, et al [13] adopted the block sparse Bayesian learning (BSBL) to solve SISO doubly selective channel estimation problem. G. Dziwoki and J. Izydorczyk, et al [14] used the measurements outside the inter block interference (IBI) free region to solve the channel estimation problem, however the frequency domain pilots were not considered. In general, most existing works conduct non-comprehensive study on doubly selective channel estimation for MIMO-OFDM system. Therefore, the relevant research work is highly significant.

III. SYSTEM MODEL

Considering an OFDM system, we focus on the synchronization and channel estimation of a SISO system. Notation CIR is the impulse response of the frequency-selective channel, which is defined as h(τ).

A. Channel Model Wide-Sense

Stationary Uncorrelated Scattering (WSSUS) model defined by Bello is currently the most commonly used model to establish the frequency-selective fading channel.

Doppler power spectrum and delay power spectrum is independent in the model. Doppler power spectrum and multipath delay power spectrum can be analyzed respectively by their own probability density function.

According to the WSSUS model, the impulse response of the frequency-selective channel h(τ) can be defined as:

$$h(\tau) = \sum_1 al \times \delta(\tau - \tau) \quad (1)$$

Where δ(·) denotes the Dirac delta function, τl and *al* are the delay and the complex amplitude of the *l*th path. Assuming the sampling space in time domain at the receiver is Ts. After spaced in the receiver, the discrete expression of CIR is h(*l*). The length of CIR is L, L = floor (τmax/Ts) (τmax is the maximum path delay). The power spectrum of the channel obeys classical power spectra, the cross-correlation function of CIR can be described as:

$$E\,[h_l \,.\, h_k{}^*\,] = \Omega l \delta(l - k) \quad (2)$$

Where δ(*l*) is a Kronecker delta function, l is the total power of the lth path, (·)∗ represents complex conjugate.

B. Training Sequence

Considering the designed training sequences in Minn's methods can improve the plateau in timing metric, we also design the training sequences with four parts. The N samples in first symbol is designed as:

$$\mathbf{S = [A\ B\ C\ D]} \qquad (3)$$

Where A = B = $Ae^{j\pi n.\ 2/(N/4)}$, C = D = $-Ae^{-j\pi n.\ 2/(N/4)}$, n is a vector n = [0, 1,..., N1 − 1] T, the denotation $\mathbf{n}^2$ represents the elements in **n** multiplied by the corresponding elements. N1 = N/4, A is the amplitude of the signal, the variance of the real and imaginary signal components is σ2 s , σ2 s = $A^2/2$.

C. Receiver Design

Considering the design of the training sequences, we design the matched filter in the receiver as:

$$F(\mathrm{k,n}) = e^{\frac{i2\pi kn}{N1}} \exp\left(-\frac{j\pi n^2}{N1}\right)/N1 \qquad (4)$$

Where k is the index in the matched filter transform domain.

Assume the frequency offset is f and the symbol timing offset is θTs (θ is an integer which can express the timing offset relative to the sampling space in time domain). We can distinguish the carrier frequency offset in two parts: an integer carrier frequency offset fI being a multiple of the subcarrier spacing, and a fractional carrier frequency offset

$$\Delta f = \Delta f_I + \Delta f_F = \varepsilon_I + \varepsilon_F) f_{sub} \qquad (5)$$

Where f sub is the spacing between subcarriers of the training sequences, f sub = $1/(N_1T_s)$. εI is an integer carrier frequency offset relative to the inverse off sub, f F is a fractional carrier frequency offset relative to the inverse off sub. Consider the design of the training sequences here N1 = N/4.

IV. SYNCHRONIZATION AND CHANNEL ESTIMATION ALGORITHMS

A. LS Estimation

In conventional comb-type pilot based channel estimation methods, the estimation of pilot signals, is based on the LS method is given by

$$\begin{aligned}\hat{H}_{p,ls} &= [H_{p,ls}(0)\ H_{p,ls}(1)\ \ldots\ H_{p,ls}(N_p-1)] \\ &= X_p^{-1}Y_p \\ &= [\frac{Y_p(0)}{X_p(0)}\ \frac{Y_p(1)}{X_p(1)}\ \ldots\ \frac{Y_p(N_p-1)}{X_p(N_p-1)}]\end{aligned} \qquad (6)$$

The LS estimate of Hp is susceptible to AWGN and Inter Carrier Interference (ICI). Because the channel responses of data subcarriers are obtained by interpolating the channel characteristics of pilot subcarriers, the performance of OFDM systems which are based on comb-type pilot arrangement is highly dependent on the rigorousness of estimate of pilot signals. Thus, a estimate better than the LS estimate is required. The MMSE estimate has been shown to be better than the LS estimate for channel estimation in OFDM systems based on block-type pilot arrangement. The Mean Square Error (MSE) estimation, shows that MMSE estimate has about 10-15 dB gain in SNR over the LS estimate for the same MSE values. The major drawback of the MMSE estimate is its high complexity, which grows exponentially with the observation samples.

B. MMSE (Minimum Mean Square Error)

In statistics and signal processing, a minimum mean square error (MMSE) estimator is an estimation method which minimizes the mean square error (MSE), which is a common measure of estimator quality, of the fitted values of a dependent variable. In the Bayesian setting, the term MMSE more specifically refers to estimation with quadratic loss function. In such case, the MMSE estimator is given by the posterior mean of the parameter to be estimated. Since the posterior mean is cumbersome to calculate, the form of the MMSE estimator is usually constrained to be within a certain class of functions. Linear MMSE estimators are a popular choice since they are easy to use, easy to calculate, and very versatile. It has given rise to many popular estimators such as the Wiener–Kolmogorov filter and Kalman filter.

There are a multitude of methods to estimate x from {zi}∀i , which can be roughly classified into statistic-based methods, e.g., maximum likelihood estimation (MLE), maximum a posterior (MAP) and minimum mean square errors (MMSE) etc, The statistic-based algorithm commonly provides an optimal parameter estimation in terms of minimum estimation errors, while the statistic-free algorithm provides a promising and simple way for estimation when the statistical knowledge of system is not available. Of course, no matter which algorithm (statistic-based or statistic-free one) we use, the unbiasedness and covariance are two important metrics for an estimator. In addition, in some specific cases with regular properties (such as linearity, Gaussian and unbiasedness, etc), some of statistics-based methods are equivalent to the statistics-free ones, just as the maximum likelihood estimation corresponds to least square estimation for linear and Gaussian system.

C. Channel Estimation of Frequency Domain

Assuming the symbol interval is much longer than the maximum channel delay spread. So the prototype function has relatively low variation in time over the interval [0,Δ], for the $\tau\epsilon[0,\Delta]$ we get

$$g(t-\tau-n\tau_0) \approx g(t-n\tau_0) \qquad (7)$$

The received pilot is rewrote as

$$\hat{a}_{m_0,n_0} = H_{m,n}\left(a_{m_0,n_0} + ja^i_{m_0,n_0}\right) + n'(t) \quad (8)$$

With the frequency domain channel estimation can be written as

$$\hat{H}_{m_0,n_0} = \frac{\ddot{a}_{m_0,n_0}}{a_{m_0,n_0} + ja^i_{m_0,n_0}} \quad (9)$$

LS, LMMSE Channel Estimation in Frequency Domain

From the equation (8), it can be rewritten as

$$\begin{aligned}\hat{a}_{m_0,n_0} &= H_{m,n}\left(a_{m_0,n_0} + ja^i_{m_0,n_0}\right) + n'(t) \\ &= H_{m,n}C_{m,n} + n'(t)\end{aligned} \quad (10)$$

Where $C_{m,n} = a_{mo.no} + ja^i_{mono}$ By analogy with the OFDM systems, we can obtain the OQAM/OFDM systems LS, LMMSE channel estimation. The LS estimation are expressed below

$$\hat{H}^{LS}_n = C_n^{-1}\hat{a}_{m_0,n_0} \quad (11)$$

Where Cn is the $M\times M$ diagonal matrix containing the samples $C_{m,n}$ on its diagonal. Different from the OFDM system, in order to perform this estimation step, a preamble of many pilot symbols is used. Likely IAM preamble structure, it depends on the value taken by $a_{m0,n0}$ and a^i_{mono} Therefore, a simpler expression of the LMMSE estimation in OQAM/OFDM as obtained

$$\hat{\mathbf{H}}^{\mathbf{LMMSE}}_{\mathbf{n}} = \mathbf{R_{hh}}\left(\mathbf{R_{hh}} + \mathbf{\Lambda}\left(\mathbf{C_n}\mathbf{C_n^H}\right)^{-1}\right)^{-1}\hat{\mathbf{H}}^{\mathbf{LS}}_{\mathbf{n}} \quad (12)$$

Where $\mathbf{R_{hh}}$ is the $M\times M$ channel covariance matrix, $\mathbf{\Lambda}$ is the $M\times M$ noise covariance matrix.

When we know a priori knowledge of channel, $\mathbf{R_{hh}}$ could be calculated. In practice, we often don't know a priori knowledge of channel. So Vincent raise low-rank approximated channel covariance matrix which don't require a priori knowledge of the channel covariance matrix

D. Channel Estimation of Time Domain

We present the channel estimation model with time domain. It uses the frequency domain pilot to estimate the time domain channel impulse responses. The discrete-time demodulated symbol can be written as

$$\begin{aligned}\hat{a}_{m_0,n_0} &= \sum_{l=0}^{L-1} h(l) \sum_{m=0}^{M-1}\sum_{n\in\mathbb{Z}}\sum_{t=-\infty}^{\infty} a_{m,n} e^{-j2\pi m v_0 l} \\ &\times g(t-l-n\tau_0)\, g(t-n_0\tau_0)\, e^{j2\pi(m-m_0)v_0 t} e^{j2\pi(m+n-m_0-n_0)} \\ &+ \sum_{t=-\infty}^{\infty} \eta(t)\, g(t-n_0\tau_0)\, e^{j2\pi m_0 v_0 t} e^{j\frac{\pi}{2}(m_0+n_0)}\end{aligned}$$

(13)

For the IOTA filter, using the IAM method preamble, the preamble pilot inserts the zero symbols between the two side to reduce the interference. For simplicity, we ignore the inter-symbol interference to preamble pilots by inserting the zero symbols in IAM method. Equation (13) can be rewritten as

$$\begin{aligned}\hat{a}_{m_0,n_0} &= \sum_{l=0}^{L-1} h(l) \sum_{m=0}^{M-1}\sum_{t=-\infty}^{\infty} a_{m,n}\, g(t-l)\, g(t)\, e^{-j2\pi m v_0 l} \\ &\times e^{j2\pi(m-m_0)v_0 t} e^{j2\pi(m-m_0)} + \sum_{t=-\infty}^{\infty} \eta(t)\, g(t)\, e^{j2\pi m_0 v_0 t} e^{j\frac{\pi}{2}m_0}\end{aligned}$$

(14)

We rewrite (14) in vector notation as

$$\mathbf{a_0} = \mathbf{\Theta h} + \mathbf{\eta_0} \quad (15)$$

Where $\mathbf{a0} = [a_{0,0}, a_{1,0}, \ldots a_{M-1,0}]^T$ is the preamble symbol vector, $\mathbf{h}$ $[h(0), h(1), \ldots, h(L)]^T$

is the L path vector of CIR, $\boldsymbol{\eta} = [\eta 0.0, \eta 1.0, \ldots \eta M-1.0]^T$ is the the noise vector, $\mathbf{\Theta}$ is an $M\times L$matrix which determined by the preamble and filter function, on the mth row and lth column is given as

$$\Theta = \sum_{m=0}^{M-1}\sum_{t=-\infty}^{\infty} a_{m,n}\, g(t-l)\, g(t) \times e^{j2\pi(m-p)v_0 t} e^{j2\pi(m-p)} e^{-j2\pi m v_0 l} \quad (16)$$

we can know that the noise is correlated between the two pilots. It is different from the OFDM system which the noise is not correlated. This is because that the orthogonality condition only holds in the real field in OQAM/OFDM systems. The noise covariance matrix is obtained as

$$\mathbf{\Lambda} = \begin{bmatrix} \sigma^2 & \sigma^2\varsigma^{1,0}_{0,0} & \cdots & \sigma^2\varsigma^{M-1,0}_{0,0} \\ \sigma^2\varsigma^{0,0}_{1,0} & \sigma^2 & \cdots & \sigma^2\varsigma^{M-1,0}_{1,0} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma^2\varsigma^{0,0}_{M-1,0} & \sigma^2\varsigma^{1,0}_{M-1,0} & \cdots & \sigma^2 \end{bmatrix} \quad (17)$$

Thus, the time domain channel estimation is an extended linear model. The LS method could be applied

$$\hat{\mathbf{h}}_{LS} = \left(\mathbf{\Theta}^H\mathbf{\Theta}\right)^{-1}\mathbf{\Theta}^H\mathbf{a_0} \quad (18)$$

LS, LMMSE Channel Estimation in Time Domain

From the above section, we set the time domain channel estimation model. The time domain LS channel estimation is applied to

$$\hat{\mathbf{h}}_{LS} = \left(\Theta^H \Theta\right)^{-1} \Theta^H \mathbf{a}_0 \tag{19}$$

The LS channel estimation doesn't need the noise and channel information. Due to its characteristic, it is a common use method. But it doesn't gain the satisfy result. When the covariance matrix of the channel is available as a priori knowledge, the LMMSE estimator could be got. So the LMMSE channel estimation of time domain is obtained as

$$\hat{\mathbf{h}}_{LMMSE} = \left(\Theta^H \Lambda^{-1} \Theta + \mathbf{R}_{hh}^{-1}\right)^{-1} \Theta^H \Lambda^{-1} \mathbf{a}_0 \tag{20}$$

As the same as the frequency domain LMMSE channel estimation, the time domain LMMSE estimator also know a priori knowledge of the noise and channel. This limits the extent of the applying. So we proposed an iterative method which don't know the accurate knowledge about the covariance matrix of channel.

E. Channel Estimation

After correlation the timing and frequency offset, the signals after a matched filter can be rewritten as:

$$\begin{cases} R^1(k) = h_l \delta(k-l) \text{A} \exp(\frac{j\pi l^2}{N_1}) + \omega_1 \\ R^2(k) = h_l * \delta(k-l) \text{A} * \exp(\frac{j\pi l^2}{N_1}) + \omega_2 \end{cases} \tag{21}$$

After compensating A, we can get the channel estimation as:

$$\begin{cases} \hat{h}1(l) = R^1(l) \exp\left(\frac{-j\pi l^2}{N_1}\right) / A_1 \\ \hat{h}2(l) = (R^2(l) \exp\left(\frac{-j\pi l^2}{N_1}\right) * / A_1 \end{cases} \tag{22}$$

The final channel estimate is taken as the average of h^1(l) and h^2(l) as: h^(l) = h^$_1$(l) + h^$_2$(l)

$$\hat{h}(l) = \left(\hat{h}_1(l) + \hat{h}_2(l)\right)/2, \quad 0 < l \le \tilde{L} \tag{23}$$

Where L˜ is the estimation length of the channel, it can be known if the channel delay spread is given. If the channel delay spread is not given, we can estimation the L˜ as follows: setting a threshold, selecting the paths whose value is larger than the threshold.

We should note that the algorithm can be used only when the length of the repeated part is larger than the maximum channel delay spread.

V. PERFORMANCE OF THE ALGORITHM

The OFDM system channel estimation was simulated with LS, MMSE, Time domain LMMSE estimation, Frequency domain LMMSE estimation, Figure.4. shows that the LMMSE algorithm improves the performance specially in low SNR values. However, at high SNR both MMSE and LMMSE show a similar performance. Furthermore, LMMSE gives better performance when compared to LS and MMSE. Nevertheless, MMSE and LS are performing same or we can tell MSE gives very marginal improvement to LS. The reason for this performance increase is because of the covariance matrix used in the TD-LMMSE. As our noise is ASWGN and it has variance of 1 so the MMSE's performance is all most that of LS algorithm

We analyse the performance of the frequency and timing domain channel estimation algorithm. The simulation results of the LMMSSE algorithm via MSE 10 to 10^{-6} and the 0 to 40 dB SNR.

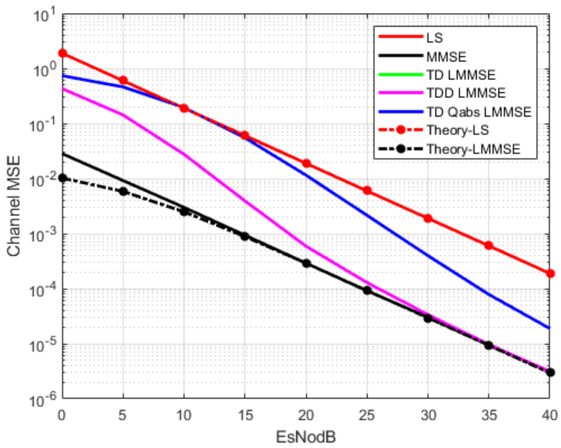

Fig.4. the LMMSE algorithm improves the performance especially in low SNR values.

VI. CONCLUSION

An algorithm has been presented for in this paper, an LMMSE channel estimation scheme. First, the frequency and the time domain channel estimation model are established. Then we review the LS and MMSE channel in frequency and time domain. Next, the LMMSE method is proposed. It builds the initial channel covariance matrix through the LS method and get the channel covariance matrix through iteration. Finally, the MMSE time domain channel estimation is obtain which no prior knowledge. The simulation show that the proposed method has a better performance compared to the LS method and has a similar performance compared to the conventional LMMSE method.

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