DELAYED DECISION FEED-BACK SEQUENCE ESTIMATION OFDM EQUALIZATION WITH CHANNEL PREDICTION

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ABSTRACT

This paper proposes a low-complexity equalizer for orthogonal frequency division multiplexing (OFDM) systems under time-varying frequency-selective fading environments. The equalization uses suboptimum maximum likelihood sequence estimation (MLSE) in cooperation with semi-blind linear prediction (SBLP) in the estimation of the channel frequency responses. When the number of pilot subcarriers is far less than the total subcarrier numbers, it reduces the Mean Square Error in the channel estimation compared to conventional linear interpolation and LMMSE (Linear Minimum Mean Square Error) algorithms. Furthermore, it doesn't require the knowledge of the statistics of the channel, which is necessary in LMMSE. In practical application, these parameters cannot be easily obtained and small estimation errors cause significant performance degradation. Theoretic analysis and simulation results demonstrate that the proposed equalizer can effectively increase the performance of OFDM receivers in time-varying fading channel.

I. INTRODUCTION

Orthogonal frequency-division multiplexing (OFDM) is a special case of multicarrier modulation with equally spaced subcarriers and overlapping spectra. The subcarrier interval is chosen such that mutual orthogonality is ensured. Several advantages over single-carrier scheme have contributed significantly to increase the popularity of OFDM in many wireless and wire-line applications. Consider the baseband time-domain signal generated by a generic OFDM system expressed as

$$x(n)=\frac{1}{\sqrt{N}}\sum_{k=0}^{N-1}X(k)e^{j2\pi nk/N}\quad n=0,1,...,N-1 \tag{1}$$

Where $X(k)$, $k=0,1,...,N-1$ denotes the frequency-domain sequence of the modulated symbols, $x(n)$ is the corresponding time-domain sequence.

When the channel is time-invariant, OFDM systems perform well. In this case, preamble symbols are used to estimate the channel frequency response, which is then used in equalizing the subsequent OFDM symbols in the packet.

However, in time-varying frequency-selective fading channel, the channel frequency response changes

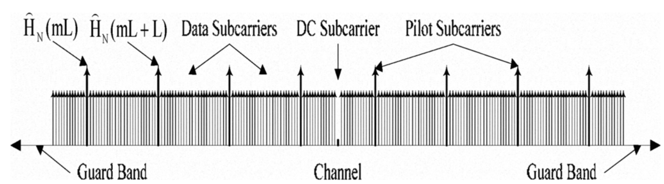

Figure 1. Subcarriers distribution pattern

from one symbol to another [1], and pilot subcarriers should be used to update channel estimations. The most commonly used channel estimation method is linear interpolation [2] [3].

As shown in Figure 1, assuming that the pilot subcarriers are evenly distributed over the whole bandwidth and the number of subcarriers between two adjacent pilot subcarriers is L, the estimation of the channel transfer function at the pilot subcarriers can be obtained as

$$\hat{H}_N(mL)=H_N(mL)+N_N(mL),\quad m=0,1,\cdots,M-1. \tag{2}$$

Where M is the number of pilot subcarriers, $\hat{H}_N(mL)$ denotes the noisy transfer function of the M pilot subcarriers （$k=mL$）, $N_N(mL)$ denotes the noise at the pilot subcarrier with frequency response $H_N(mL)$. Channel estimation over the whole N subcarriers（k = 0, … ,N-1）can then be obtained by linear interpolation.

Without loss of generality, if a first-order linear interpolation is used, the linear interpolation relation is

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$$\hat{H}_N(k) = \hat{H}_N(mL+i) = \left(1-\frac{i}{L}\right)\hat{H}_N(mL) + \frac{i}{L}\hat{H}_N(mL+L)$$
$$= \left[\left(1-\frac{i}{L}\right)H_N(mL) + \frac{i}{L}H_N(mL+L)\right] +$$
$$\left[\left(1-\frac{i}{L}\right)\cdot N_N(mL) + \frac{i}{L}\cdot N_N(mL+L)\right]$$
$$i = 1,2,\ldots,L-1 \qquad (3)$$

Where $H_N(k)$ is the value of the transfer function for the k = mL+i subcarrier, which is between those two neighboring pilot subcarriers with transfer function $\hat{H}_N(mL)$ and $\hat{H}_N(mL+L)$. Since other pilot subcarriers are located significantly further away from these interpolated subcarriers than two neighboring pilot subcarriers, the performance mainly depends on those two neighboring pilot subcarriers. The term in the first square brackets in (3) is the desired estimation, provided that every segment of the channel transfer function between adjacent pilot subcarriers is ramp-like. Unfortunately, this assumption does not hold for most of the cases. This model mismatch forms a part of the estimation error. So, linear interpolation has the lowest complexity at the cost of performance.

Linear minimum mean square error (LMMSE) [4] provides better channel estimation. From the linear interpolation described above, it can be observed that the frequency responses at close neighboring subcarriers are linearly dependent. Therefore, it is possible to interpolate the channel frequency response based on the correlation coefficients among those subcarriers, instead of those fixed coefficients dependent on subcarrier index k in linear interpolation, as show in (3).

According to [5] [6], the LMMSE channel estimation can be described as:

$$\hat{H}_{N\_LMMSE}(k) = R_{HHp}\left(R_{HpHp} + \frac{\beta}{SNR}I\right)^{-1}\hat{H}_{LS} \qquad (4)$$

Where $R_{HHp} = E[HH_p{}^H]$, $R_{HpHp} = E[H_pH_p{}^H]$, H denotes the channel transfer function, H_p denotes the channel transfer function at the pilot subcarriers. $\hat{H}_{LS}$ is the Least-Square estimation of H_p; β is a constant dependent on the signal constellation.

After the channel estimation $\hat{H}_{N\_LMMSE}(k)$ is obtained, it can be used directly in the frequency domain equalization to detect the symbols in the subcarriers.

LMMSE algorithm requires the knowledge of the statistics of the channel, e.g. R_{HHp}, R_{HpHp}, and SNR. In practical applications, these parameters cannot be easily obtained. Furthermore, they might cause significant degradation when the statistics of the channel change.

Furthermore, when the number of pilot subcarriers M is far less than the total number of subcarriers N, both linear interpolation and LMMSE will be subject to significant performance degradation, because, for channel frequency response, the linear dependency or correlation between pilot subcarrier and data subcarriers are very small, it results in inaccurate interpolation and estimation. However, the linear dependency between neighboring subcarriers can be exploited. It is well known that the correlation coefficients are maximized between closest neighboring subcarriers. So, the most accurate channel prediction is given by the linear combination of channel frequency response at the closest neighboring subcarriers.

Given that the channel frequency response at subcarrier k-1 and k-2 are H(k-1) and H(k-2), the channel frequency response value at subcarrier k can be predicted as:

$$H(k) = p(1)H(k-1) + p(2)H(k-2)$$

Where p(1) and p(2) are the coefficients of a linear prediction filter.
Based on this, a novel approach is proposed in this paper, which combines the channel prediction with DDFSE equalization by using a decision feed-back algorithm.

The paper is organized as follows. In Section II, the system model and underlying theories are described. In Section III, performance analysis and upper-bound are provided. In Section IV, the results of simulation are shown to compare the proposed scheme with traditional schemes. Section V includes the conclusions of the proposed algorithm.

II. SYSTEM MODEL

The system model for the proposed scheme is described in Figure 2.

The proposed DDFSE equalizer mainly consists of two parts: equalization and demodulation and channel prediction. The equalization and demodulation block is based on the DDFSE, which is a sub-optimum MLSE algorithm. By using this algorithm, the equalizer can generate soft outputs for the channel decoder. On the other hand, the channel prediction module can be regarded as an integral part of the equalizer, and it uses the decision feed-back generated by the equalizer to predict the channel frequency response in every subcarrier. So the equalization and channel prediction work alternatively and

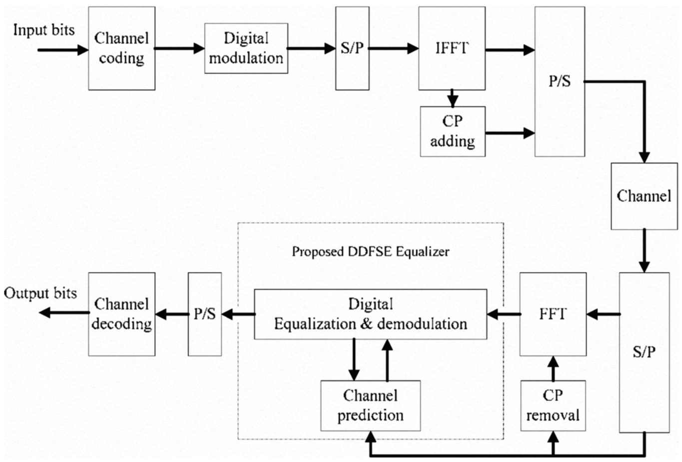


Figure 2. System Block Diagram

cooperatively. These two modules will be discussed in the following subsections.

A. DDFSE equalization and demodulation

Suppose that Y(k) is the input to the equalizer, then

$$Y(k) = H(k)X(k) + N(k)\,,\ \ k = 0,1,2,...,N-1 \tag{5}$$

Where X(k) is the transmitted symbols, H(k) is the channel transfer function, N(k) is the noise and N is the number of subcarriers.

Given the received sequence Y(k) and channel transfer function H(k), the MLSE algorithm estimates the sequence X(k) that maximizes the *likelihood function* $\phi(y\,|\,x)$ (the conditional probability density function of the output y given the input x). Let the metric M of X(k) be

$$M = \|Y(k) - H(k)X(k)\|^2 \tag{6}$$

Since M is proportional to the log likelihood function $-\log[\phi(y\,|\,x)]$, the sequence $\hat{X}(k)$ that minimizes the metric M, is the solution to the maximum likelihood sequence estimation problem [7] [8].

The rational function $\breve{H}(k)$ can be described in terms of a state machine with state space S. The DDFSE algorithm simplifies the MLSE by decomposing the state space S into two subspace: U and V. If μ is the reduced memory of the channel

$$\begin{aligned}\breve{H}(k) &= \left[\tilde{H}(k-1), \tilde{H}(k-2), ..., \tilde{H}(k-\hat{l})\right] \\ &= \left[\frac{Y(k-1)}{X(k-1)}, \frac{Y(k-2)}{X(k-2)}, ..., \frac{Y(k-\hat{l})}{X(k-\hat{l})}\right]\end{aligned} \tag{7}$$

$p = [p(1)\ \ p(2)\ \ \cdots\ \ p(\hat{l})]^T$ is the fixed prediction filter with length $\hat{l}$, the estimated received signal can be written as

$$\begin{aligned}\hat{Y}(k) &= X(k)\cdot\hat{H}(k) \\ &= X(k)\left(\sum_{i=1}^{\mu+1} H(k-i)p(i) + W(k)\right) + N(k)\end{aligned} \tag{8}$$

Where $W(k) = \sum_{i=\mu+2}^{\hat{l}} H(k-i)p(i)$ is the component derived from the delayed decision feedback, N(k) denotes the noise component.

At time k, the state of the U subspace can be denoted as

$$u_k = [X(k-1), ..., X(k-\mu)]$$

And the state of the V subspace is

$$v_k = [X(k-\mu-1), ..., X(k-l)]$$

The DDFSE algorithm combines the structure of the Viterbi algorithm and the decision feed-back detector. As in the Viterbi algorithm, it uses a state machine description of the channel $\breve{H}(k)$ to recursively estimate the best path in the trellis while storing only one path for each state. But since each state of the DDFSE trellis provides only partial information about the full state of the channel, the algorithm also uses the best path leading to each state to compute the metric.

Obviously, the alphabet size of X(k) and the dimension of U subspace (μ here) determine the number of states in the trellis, thus decide the computational complexity. The V subspace is composed of the decided symbols in each path. An estimation of the partial state in the V subspace store the 'feed-back information' extracted from the best path. Similar to a decision feed-back detector, these estimations are from past inputs that are greater than the μ samples in the past.

Note that if U = S, the algorithm reduces to the Viterbi algorithm, if V = S, the algorithm is equivalent to the zero-forcing decision feed-back detection. If Soft Output Viterbi Algorithm (SOVA) is used to generate a soft-bit output in DDFSE [9] [10], it will further improve the performance of the DDFSE algorithm.

From the discussion above, it can be concluded that the prediction of $\hat{H}(k)$ plays an important role in the whole system. Thus, in the following section, an algorithm on computing the prediction filter coefficients $p = [p(1)\ \ p(2)\ \ \cdots\ \ p(\hat{l})]^T$ will be introduced.

B. Decision feed-back semi-blind linear channel prediction

The function of this linear prediction algorithm is to obtain the prediction filter coefficients $p = [p(1)\ \ p(2)\ \ \cdots\ \ p(\hat{l})]^T$ based on decision feed-back. Since this approach takes advantage of the channel frequency response components obtained at the pilot subcarriers, it is semi-blind.

Assume that the prediction filter is P(z),

$$P(z) = \sum_{k=1}^{\hat{l}} p(k) z^{-k} \tag{9}$$

Where the $\hat{l}$ is the length of prediction filter.
The prediction filter P(z) is designed to minimize the output power of the prediction error. The optimum coefficients for this criterion are given by solving the Yule-Walker equations [11]

$$\Phi \overline{p} = \overline{\phi} \tag{10}$$

With

$$\Phi = \begin{bmatrix} \phi[0] & \phi[-1] & \cdots & \phi[-(\hat{l}-1)] \\ \phi[1] & \phi[0] & \cdots & \phi[-(\hat{l}-2)] \\ \vdots & \vdots & \ddots & \vdots \\ \phi[\hat{l}-1] & \phi[\hat{l}-2] & \cdots & \phi[0] \end{bmatrix}$$

$$\overline{p} = [p(1)\ \ p(2)\ \ \cdots\ \ p(\hat{l})]^T$$

$$\overline{\phi} = [\phi(1)\ \ \phi(2)\ \ \cdots\ \ \phi(\hat{l})]^T$$

$$\phi(k) = \vec{H}(k) \otimes \vec{H}^*(-k)$$

Where $(\cdot)^T$ and $\otimes$ denote transposition and convolution, respectively. $\vec{H}(k)$ is the channel frequency response estimation. $\phi[-(\hat{l}-1)] = \phi^*[\hat{l}-1]$. The length of sequence $\vec{H}(k)$ is $\hat{l}$.
These equations can be solved by using the Levinson-Durbin (LD) algorithm, which only requires $\hat{l}^2 + O(\hat{l}^2)$ operations. The LD Algorithm recursively calculates a predictor with a desired order $\hat{l}$ by determining all predictors of order $< \hat{l}$.

After obtaining the prediction filter P(z), the prediction value of the channel frequency response $\hat{H}(k)$ can be found out at every sub-carrier k, based on the U subspace and V subspace of the DDFSE equalizer. The coefficients of the prediction filter P(z) will be updated along each survivor path using the algorithms previously discussed.

C. Description of the algorithm and sub-optimum algorithm

The recursive steps of the proposed algorithm involve the following.

1. Initiate $\vec{H}(0)$ based on channel estimation.
2. At time k（k = 0,…,N-1）, use (6), (8) to obtain metric M for every state.
3. Based on each survivor path, update $\vec{H}(k+1)$ and $\overline{p}$ using (7) and (10).
4. Move on to the next time k+1 and go to step 2 to repeat the same procedure until k=N-1.
5. Retrace back along the final survivor path to obtain the output equalized symbols or bits.

The procedure of updating $\overline{p}$ in step 3 involves a large amount of computation. To reduce the computation complexity, a practical sub-optimum approach is developed. Instead of updating the prediction filter along each survivor path, a fixed prediction filter is used to take advantage of the trellis structure of the DDFSE equalizer.

Since the frequency domain range is $[-\pi, \pi]$, the prediction with direction from $-\pi$ to π can be defined as forward prediction. In the same way, the backward prediction is in direction from π to $-\pi$. At every state, the equalizer finds out the best path that minimizes the summation of the powers of the forward prediction error and backward prediction error. This rule is similar to that used in Burg's algorithm [12]. To serve this purpose, some changes in the definition of the metric M are made.

If $p = [p(1)\ \ p(2)\ \ \cdots\ \ p(\hat{l})]^T$ is the fixed prediction filter with length $\hat{l}$, at sub-carrier k, the forward prediction of the channel frequency response is $\hat{H}_f(k)$, and the backward prediction is $\hat{H}_b(k)$. The previous forward and backward channel frequency response estimations are $\vec{H}_f = \left[\tilde{H}_f(k-1), \tilde{H}_f(k-2), ..., \tilde{H}_f(k-\hat{l})\right]$ and $\vec{H}_b = \left[\tilde{H}_b(k+1), \tilde{H}_b(k+2), ..., \tilde{H}_b(k+\hat{l})\right]$ respectively, thus

$$\hat{H}_f(k) = \sum_{n=1}^{\hat{l}} p(n) * \tilde{H}_f(k-n),$$

$$\hat{H}_b(k) = \sum_{n=1}^{\hat{l}} p(n) * \tilde{H}_b(k+n) \tag{11}$$

Then the equation of the metric M can be expressed as

$$\begin{aligned} M &= \left\|Y(k) - \hat{H}_f(k)X(k)\right\|^2 + \left\|Y(k) - \hat{H}_b(k)X(k)\right\|^2 \\ &= \left[\left\|H(k) - \hat{H}_f(k)\right\|^2 + \left\|H(k) - \hat{H}_b(k)\right\|^2\right] \cdot \left\|X(k)\right\|^2 \\ &= \left[\left\|e_f\right\|^2 + \left\|e_b\right\|^2\right] \cdot \left\|X(k)\right\|^2 \end{aligned} \tag{12}$$

Where $e_f = H(k) - \hat{H}_f(k)$ is the forward prediction error; and $e_b = H(k) - \hat{H}_b(k)$ is the backward prediction error. The maximum likelihood solution to the equation above can be used to minimize the summation power of the forward and backward prediction errors.

For forward prediction, based on every state in the space S: $s_b^k = (x_k, x_{k-1}, ..., x_{k-l+1})$, the updated forward channel frequency response estimation is

$$\left[\tilde{H}_f(k), \tilde{H}_f(k-1), ..., \tilde{H}_f(k-\hat{l}+1)\right] = \left[\frac{Y(k)}{X(k)}, \frac{Y(k-1)}{X(k-1)}, ..., \frac{Y(k-\hat{l}+1)}{X(k-\hat{l}+1)}\right] \quad (13)$$

It can be observed that this is the updated value of (7). The backward channel frequency response estimation is updated in the same way.

As an example, when the transmitted symbols are from a 4-alphabet set $\{X(i)\}, i = 0,1,2,3$, and $\hat{l} = 2$, $\mu = 1$, Figure 3 shows a forward path through the trellis of the proposed approach with partial state estimations for states along the path.

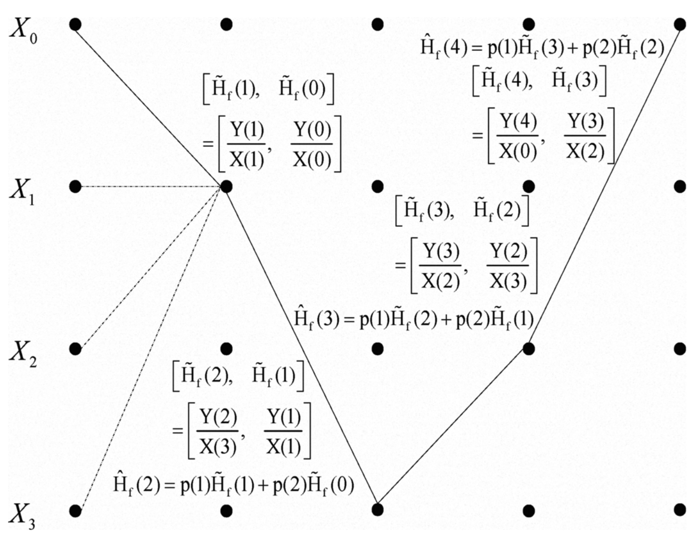


Figure 3. A path through the trellis of the proposed equalization approach

In Figure 3, the dashed lines indicate possible transfer branches between the states, the solid lines denote remaining path. Since $\mu = 1$, the state space of the trellis is U subspace, which is 4-state set $\{X(i)\}, i = 0,1,2,3$. The prediction filter is $p = [p(1) \quad p(2)]^T$. $\hat{H}_f(k)$ is the forward prediction of the channel frequency response, which is used to compute branch metric M with (12). Only $\tilde{H}_f(k)$ is the new term in the updated forward channel frequency response estimation. $\tilde{H}_f(k-1)$ could be obtained from the partial state estimations(decision feedback), which belong to the V subspace.

Hence, according to the procedure described above, the computation complexity of the proposed approach is $2M_a^\mu \cdot O(N)$, where M_a is the alphabet size of modulation on each subcarrier and N is the number of subcarrier.

III. PERFORMANCE ANALYSIS AND UPPER-BOUND

The linear and LMMSE interpolation error can be defined by

$$e_{int}(k) = H_N(k) - \hat{H}_N(k) \quad (14)$$

Then

$$\begin{aligned} &E[\|e_{int}(mL+1)\|^2], E[\|e_{int}((m+1)L-1)\|^2] \\ &\le E[\|e_{int}(mL+2)\|^2], E[\|e_{int}((m+1)L-2)\|^2] \\ &\le ... \le E[\left\|e_{int}(mL+\left\lceil \frac{L}{2} \right\rceil)\right\|^2] \end{aligned} \quad (15)$$

Where $\lceil \ \rceil$ denotes the function that rounds its argument up to the next integer.
With the proposed channel prediction approach, the prediction error is

$$e_{pre}(k) = H_N(k) - \hat{H}_N(k) \quad (16)$$

By using Decision Feed-Back Estimation (DFE),

$$\begin{aligned} &E[\|e_{pre}(mL+l)\|^2] \cong E[\|e_{int}(mL+l)\|^2], E[\|e_{int}((m+1)L-l)\|^2] \\ &l = 1,2,...,L-1 \end{aligned} \quad (17)$$

Therefore,

$$E[\|e_{pre}(mL+l)\|^2] \le \frac{1}{N}\sum_{k=0}^{N-1} E[\|e_{int}(k)\|^2] \quad (18)$$

With (12), when $E\left[\|e_f\|^2 + \|e_b\|^2\right]$ is minimized, $E[\|e_{pre}(mL+l)\|^2]$ obtains minimum value $\mathrm{Min}\left\{E[\|e_{pre}(mL+l)\|^2]\right\}$.

The upper bound of symbol error probability for DDFSE equalization is given by [10]

$$P_M = Q\left[\sqrt{2}\frac{\|d_{min}\|}{\sqrt{N_0}}\right] \sum_{\lambda \in \Lambda_{d_{min}}} w(\lambda) \prod_{i=0}^{n-1} \frac{m - \|e_i\|}{m} \quad (19)$$

Where the integer m is the number of the input alphabet, the input sequence error is $e(i) = x(i) - \hat{x}(i)$, $x(i)$ and $\hat{x}(i)$ are the input sequence and the estimation produced by the algorithm. d_{min} is the minimum distance achieved by an error event of the DDFSE trellis. $w(\lambda)$ is the number of symbol errors entailed by an error event λ, n is the duration of an error event λ.
So when $m = M, \mu = 1, n = 1$

$$P_M = Q\left[\sqrt{2}\frac{\|d_{min}\|}{\sqrt{N_0}}\right] \quad (20)$$

Where $N_0 = \sigma^2 + N_{ICI} + \mathrm{Min}\left\{E[\|e_{pre}(mL+l)\|^2]\right\}$, σ^2 is AWGN power, N_{ICI} is Inter Channel Interference power.
The upper bound of symbol error probability for one tap linear equalization is given by [10]

$$P'_M = \frac{2(M-1)}{M}Q\left[\frac{\|f_{avr}\|}{\sqrt{N'_0}}\right] \quad (21)$$

Where $N'_0 = \sigma^2 + N_{ICI} + \frac{1}{N}\sum_{k=0}^{N-1}E[\|e_{int}(k)\|^2]$, f_{avr} represents the mean value of the estimated channel frequency responses, then $\|d_{min}\|^2 \approx \|f_{avr}\|^2$.
Obviously, it can be concluded from (20) and (21) that $P_M < P'_M$, as long as $\sigma^2 + N_{ICI} \ll \mathrm{Min}\left\{E[\|e_{pre}(mL+l)\|^2]\right\}$. It means low level AWGN and Inter Channel Interference (ICI) power.
So, in order to suppress the noise power, the length of prediction filter, $\hat{l}$, should not be too large. As for the dimension of U subspace, μ, it could be an arbitrary integer in $[1,\hat{l}]$. Although increasing μ means more states in trellis and better performance, it also brings about significantly extra computation complexity. It should be determined by trade-off between these two metrics.

IV. SIMULATION RESULTS

In this section, the performance of the proposed approach will be studied in a wireless time-variant Rayleigh channel. The sampling rate is 10MHz, the digital modulation scheme is 16QAM, the number of subcarrier is 256, and the carrier frequency is 2.3 GHz [13], the Doppler spread f_D is 200 Hz and 400 Hz respectively. As showed in Table 1, the propagation parameters are in accordance with the model of ITU-R M.1225 vehicular test environment Channel A, which is widely used for performance evaluation in both UMTS and IEEE 802.16.

Table 1. ITU-R M.1225 Vehicular Channel A Environment

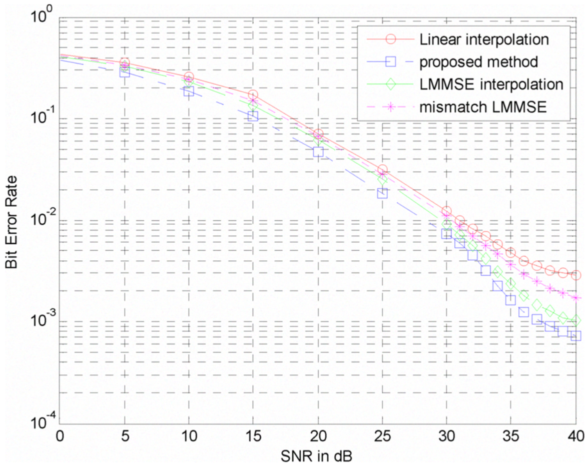
Tap	Relative delay (ns)	Average power (dB)
1	0	0.0
2	310	-1.0
3	710	-9.0
4	1090	-10.0
5	1730	-15.0
6	2510	-20.0

In simulation, 192 subcarriers are used to transmit data symbols, 8 subcarriers are used to transmit pilot symbols. The length of the prediction filter P(z) is $\hat{l} = 2$. As for the parameters for U and V subspaces, $\mu = 1$ is used. The bit error rate under different Signal to Noise power Ratio is shown in Figure 4 (a) and (b).

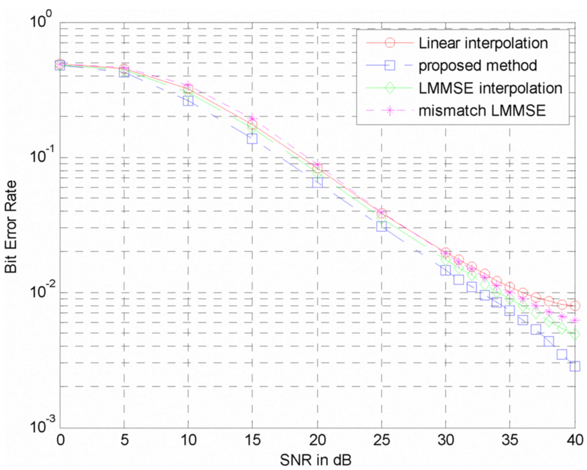
From Figure 4, for 10^{-3} bit error rate, it can be found that the proposed equalization method brings about a processing gain over LMMSE interpolation, which is approximately 4 dB for F_d = 200 Hz and 1.5 dB in case of F_d = 400 Hz.

Compared to the ideal LMMSE algorithm, the proposed equalization method provides better performance. Since the number of pilot subcarriers is far less than that of data subcarriers, LMMSE is not so effective and its performance cannot be obtained in real applications. The mismatch LMMSE is the case where statistical parameters (for example, R_{HHp}, R_{HpHp} and SNR) used in the channel estimation have statistical error compared to real value. It is common in practical applications. Obviously, the performance degrades significantly.

The new equalization approach proposed in this paper does not require any pre-knowledge on the statistics of the channel, thus secures the robustness of the system performance. Furthermore, it does not introduce any overhead, so it will not reduce the efficiency of the system. It can provide more performance gain at relatively high SNR. In this case, the Mean Square Error (MSE) of the channel estimation plays a more important role than white noise in deciding the performance of the equalization. It is a typical scenario in MIMO-OFDM systems [14]. The proposed approach will be beneficial to those MIMO-OFDM systems.



(a) BER performance for $F_d = 200$ Hz



(b) BER performance for $F_d = 400$ Hz

Figure 4. BER performance under different SNR

V. CONCLUSIONS

In this work, a novel equalization algorithm that is suitable for multicarrier transmission over rapidly time-varying channels is proposed. Analysis and simulation show that it out-performs the traditional equalizer, - commonly employed in OFDM systems. The extra computational cost introduced by this algorithm is also reasonable.

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