LOW COMPLEXITY ITERATIVE METHOD OF SIGNAL DETECTION IN OFDM DOUBLY SELECTIVE CHANNELS

[†]*Sajid Ahmed,* [†]*Mathini Sellathurai ,*[‡]*Sangarapillai Lambotharan and* [†] *Jonathon Chambers*

[†] Centre of Digital Signal Processing Cardiff University, Cardiff CF24 OYF, Wales, UK
Phone: +44 29 2087 9057, email: *ahmeds6, sellathuraiM, chambersJ@cf.ac.uk,*[‡]*s.lambotharan@kcl.ac.uk*

ABSTRACT

Time selectivity of the channel causes inter-carrier interference (ICI) in orthogonal frequency division multiplexing (OFDM), thereby degrading the system performance significantly and increasing the computational complexity of the receiver. On the other hand, time selectivity introduces temporal diversity that can be exploited to improve the performance of the receiver. In this work, a new method is presented to compensate for the effects of time selectivity of the channel that exploits the sparsity present in the channel convolution matrix (CCM). Here, working with time and frequency domain samples, a low complexity iterative algorithm is proposed. Simulation results show the superior performance over the standard linear minimum mean square error (L-MMSE) equalizer with the advantage of computational saving and temporal diversity gain.

1. INTRODUCTION

OFDM is a technology that transmits multiple low-rate signals simultaneously over a single transmission path. Low symbol rate makes OFDM resistant to the effects of inter-symbol-interference (ISI) caused by multi-path propagation. The effects of ISI on an OFDM signal can be further improved by the addition of a guard period to the start of each symbol in the time domain and hence yields more robustness to multi-path fading. The guard period is generally a cyclic copy of the last bits of the actual data being transmitted. The length of the cyclic prefix is kept at least equal to the channel order; under this condition, a linear convolution of the transmitted sequence and the channel is converted to a circular convolution. Moreover, the approach enables the receiver to use the fast Fourier transform (FFT) for OFDM implementation [1]. In OFDM the overall system bandwidth is broken up into N orthogonal sub-carriers, the data are transmitted on these sub-carriers resulting in a symbol rate that is N times lower than that of a single carrier system. Orthogonal spacing among the carriers prevents the demodulator from seeing frequencies other than their own. One of the principal disadvantages of OFDM is that it is very sensitive to time selectivity of the channel that introduces frequency dispersion, i.e. loss of orthogonality between the sub-carriers. Time selectivity of the channel makes it difficult to benefit from the simple equalization of OFDM that requires only N computations and degrades the bit error rate (BER) performance. Mitigating time selectivity of the channel using an L-MMSE equalizer is discussed in [2, 3]; the complexity of the L-MMSE equalizer is however $\mathscr{O}(N^2)$ and yields poor performance which makes it impractical for large N. In [4], Philip Schniter proposed that pre-processing the received samples by multiplying with window coefficients renders the ICI response sparse, and thereby squeezes the significant coefficients into the $2D+1$ central diagonals of an ICI matrix. Here, it is found that $D = f_d N + 1$, where f_d is the Doppler shift (DS) in the carrier frequency and N is the number of carriers used to transmit an OFDM symbol. The complexity of this algorithm also increases as the DS increases. In contrast to this work, if we examine the time domain model of the received OFDM signal, the CCM is already sparse and has similar structure to that after preprocessing of the received samples in [4]. Here, the number of non-zero elements in a row depends on the length of channel taps, L, which for a wireless channel is typically equal to 5. In higher scattering environments, channel shortening algorithms can be used to shorten the channel length [5]. This characteristic of the CCM can help to design a low complexity OFDM equalizer for doubly selective channels. Therefore, working with both time and frequency domain samples a low complexity iterative algorithm is proposed that requires no pre-processing and the complexity is independent of the DS.

The paper is organized as follows; in the following section the signal model is presented. Then, in Section 3, we study the symbol estimation that is based on an MMSE equalizer and iterative refining. In section 4, we discuss the complexity of the algorithm. Simulation results are given in section 5, followed by our conclusions in Section 6.

Notations: Bold upper case $\mathbf{X}$ denotes a matrix and lower case $\mathbf{x}$ a vector. The n-th row and l-th column entry of a matrix $\mathbf{X}$ is denoted by $\mathbf{X}_{n,l}$. The Conjugate and conjugate transposition of a matrix are respectively denoted by $(.)^*$ and $(.)^H$; $\mathbf{I}_N$ is an identity matrix of size N, and $\mathbf{i}_k$ represents its $k-th$ column. $Pr\{.\}$ and $p\{.\}$ respectively denote the probability of the discrete and continuous event in the bracket. $E\{.\}$, $Re\{.\}$, and $\langle . \rangle_N$ denote respectively statistical expectation, the real part of a complex number and the modulo-N operation. Finally, we use $\{x(n)\}$ to denote the sequence $x(n)$ of N symbols where $n = 0, 1, \cdots, N-1$ and $\text{Cov}[x(n), y(n)]$ to denote the covariance between $x(n)$ and $y(n)$.

2. PROBLEM STATEMENT

The basic baseband OFDM transmission and reception model is given in Figure 1. First of all a data block of N symbols is converted into the time domain by taking its inverse FFT (IFFT). Before transmission a cyclic prefix is appended at the beginning of the time samples. The whole block of data is termed as an OFDM symbol. At the receiver the cyclic prefix is removed from the received time samples and the FFT is performed to convert the time domain samples into the frequency domain samples. If the symbols $\{s(k)\}$ are i.i.d and $\{x(n)\}$ are the corresponding time domain samples after performing the IFFT, then the relationship between $x(n)$

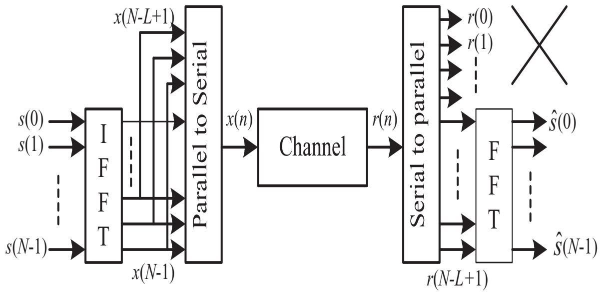

Figure 1: A basic baseband OFDM system, transmitting subsequent blocks of N complex data.

and $s(k)$ can be described by the following N-point inverse discrete Fourier transform (DFT) operation

$$x(n) \;=\; \frac{1}{\sqrt{N}}\sum_{k=0}^{N-1} s(k)e^{j\frac{2\pi}{N}kn}. \tag{1}$$

The time domain samples, $\{x(n)\}$, in vector form can be written as $\mathbf{x} = \mathbf{F}^H\mathbf{s}$, where $\mathbf{F}$ is the DFT matrix of size N. We assume that the signal $x(n)$ has propagated through L different paths and the sampling rate is equal to the symbol transmission rate. The received baseband signal at time n after removing the cyclic prefix can be written as

$$r(n) = \sum_{l=0}^{L-1} h(n,l)x(\langle n-l\rangle_N) + v(n), \tag{2}$$

where $h(n,l)$ is the unknown complex channel gain (CG) for the lth channel tap and $v(n)$ is the complex white Gaussian noise with variance σ^2 at sample time n. The estimation of linear time-variant (LTV) and linear time-invariant (LTI) channels is discussed respectively in [3] and [6]. Here, throughout this paper we assume perfect knowledge of CGs. The time domain received samples in vector form can be written as

$$\mathbf{r} \;=\; \mathbf{Hx}+\mathbf{v} = \mathbf{HF}^H\mathbf{s}+\mathbf{v} \tag{3}$$

where $\mathbf{H}$ is the CCM and $\mathbf{H}_{n,l} = h(n, \langle n-l\rangle_N)$. After performing the FFT on (3) the frequency domain received samples can be written as

$$\gamma \;=\; \mathbf{FHF}^H\mathbf{s}+\mathbf{Fv} = \mathbf{H}_{df}\mathbf{s}+\mathbf{Fv}. \tag{4}$$

In (4), if the channel is LTI then the matrix $\mathbf{H}_{df}$ will be diagonal and to find the L-MMSE equalizer for the estimation of symbols $\{s(k)\}$ will require the inverse of a diagonal matrix, which is computationally inexpensive. But, if the channel is LTV then the matrix $\mathbf{H}_{df}$ will no longer be diagonal, which thereby introduces ICI. Now an L-MMSE equalizer will require the inversion of an $N\times N$ Hermitian matrix that needs $\mathscr{O}(N^2)$ operations that is infeasible for large N and yields poor BER performance [3]. However, as shown in Figure 2, if modulo-N indexing is assumed then the structure of $\mathbf{H}$ reveals that the time domain sample $x(n)$ contributes only to the observation samples $r(n)$ to $r(n+L-1)$. Therefore, these are the only samples required to estimate $x(n)$ and in vector form they can be written as, $\mathbf{r}_n = \mathbf{H}_n\mathbf{x}+\mathbf{v}_n$ where

$$\mathbf{r}_n \;=\; \begin{bmatrix} r(n) & r(n+1) & \cdots & r(n+L-1) \end{bmatrix}^T,$$

$$\mathbf{H}_n \;=\; \begin{bmatrix} \mathbf{H}_{n,0} & \mathbf{H}_{n,1} & \cdots & \mathbf{H}_{n,N-1} \\ \mathbf{H}_{n+1,0} & \mathbf{H}_{n+1,1} & \cdots & \mathbf{H}_{n+1,N-1} \\ \vdots & \cdots & \cdots & \vdots \\ \mathbf{H}_{n+L-1,0} & \mathbf{H}_{n+L-1,1} & \cdots & \mathbf{H}_{n+L-1,N-1} \end{bmatrix},$$

and $\mathbf{v}_n = \begin{bmatrix} v(n) & v(n+1) & \cdots & v(n+L-1) \end{bmatrix}^T$. Note that in $\mathbf{H}_n$ matrix $\mathbf{H}_{n,p} = 0$ when $p \geq L$.

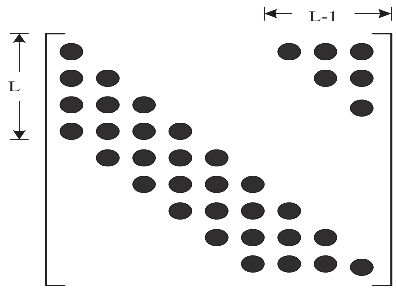

Figure 2: Diagonal structure of the time-domain CCM $\mathbf{H}$.

3. SYMBOL ESTIMATION

Our goal is to estimate the transmitted symbols, $\{s(k)\}$, however, their direct estimation is computationally expensive and yields poor BER performance. In this work, an indirect approach is used, first the time domain samples, $\{x(n)\}$, are estimated and then used to maximize the a posteriori values of symbols $\{s(k)\}$ with an iterative algorithm.

3.1 MMSE Equalizer

To estimate the samples $\{x(n)\}$ an MMSE equalizer is used. Since the noise is uncorrelated $E\{\mathbf{v}_n\} = \mathbf{0}$, $E\{\mathbf{v}_n{\mathbf{v}_n}^H\} = \sigma^2\mathbf{I}_L$ and $E\{x(n)\mathbf{v}_n\} = \mathbf{0}$. The MMSE equalizer $\mathbf{w}_n$, of length L for the soft estimates of $x(n)$ can be derived by minimizing the cost function

$$J(\mathbf{w}_n) = E\{(x(n)-\mathbf{w}_n^H\mathbf{r}_n)(x(n)-\mathbf{w}_n^H\mathbf{r}_n)^H\},$$

which yields the equalizer coefficient values (when $\bar{x}(n)\neq 0$) given by [7]

$$\mathbf{w}_n = \left(\mathbf{H}_n\mathrm{Cov}(\mathbf{x},\mathbf{x})\mathbf{H}_n^H+\sigma^2\mathbf{I}_L\right)^{-1}\mathbf{H}_n\mathrm{Cov}(\mathbf{x},x(n)) \tag{5}$$

and the estimate $\hat{x}(n) = \bar{x}(n)+\mathbf{w}_n^H(\mathbf{r}_n-\mathbf{H}_n\bar{\mathbf{x}})$, (6)

where $\bar{x}(n) = E\{x(n)\}$, and $\bar{\mathbf{x}} = E\{\mathbf{x}\}$. Equations (5) and (6) can be used to estimate the values of $\hat{x}(n)$. If we know the samples $\{x(n)\}$ then the symbol $s(k)$ can be found as

$$s(k) \;=\; \mathbf{i}_k^H\mathbf{Fx} = \mathbf{i}_k^H\mathbf{F}\sum_{n=0}^{N-1}\mathbf{i}_n x(n)$$

therefore the equalizer can be translated in terms of the covariance of $\mathbf{s}$ to yield

$$\mathbf{w}_n = \left(\mathbf{H}_n\mathbf{F}^H\mathrm{Cov}(\mathbf{s},\mathbf{s})\mathbf{FH}_n^H+\sigma^2\mathbf{I}_L\right)^{-1}\mathbf{H}_n\mathbf{F}^H\mathrm{Cov}(\mathbf{s},\mathbf{s})\mathbf{Fi}_n. \tag{7}$$

Similarly, the estimate of $s(k)$ becomes

$$\begin{aligned}\hat{s}(k) &= \mathbf{i}_k^H \mathbf{F} \sum_{n=0}^{N-1} \mathbf{i}_n \hat{x}(n) \\ &= \mathbf{i}_k^H \mathbf{F} \sum_{n=0}^{N-1} \mathbf{i}_n \left[\bar{x}(n) + \mathbf{w}_n^H (\mathbf{r}_n - \mathbf{H}_n \bar{\mathbf{x}})\right] \\ &= \bar{s}(k) + \mathbf{i}_k^H \mathbf{F} \sum_{n=0}^{N-1} \mathbf{i}_n \mathbf{w}_n^H (\mathbf{r}_n - \mathbf{H}_n \mathbf{F}^H \bar{\mathbf{s}}). \qquad (8)\end{aligned}$$

If we suppose that $\mathscr{V}$ be the vector of dimension $N \times 1$ of frequency domain noise samples then,

$$\mathbf{v}_n = \begin{bmatrix} \mathbf{i}_n^H \\ \mathbf{i}_{n+1}^H \\ \vdots \\ \mathbf{i}_{n+L-1}^H \end{bmatrix} \mathbf{F}^H \mathscr{V} = \Lambda_n \mathbf{F}^H \mathscr{V}$$

Let $\mathbf{Q} = \mathbf{F}\sum_{n=0}^{N-1} \mathbf{i}_n \mathbf{w}_n^H \mathbf{H}_n \mathbf{F}^H$ and $\mathbf{P} = \mathbf{F}\sum_{n=0}^{N-1} \mathbf{i}_n \mathbf{w}_n^H \Lambda_n \mathbf{F}^H$ then (8) can be written as

$$\hat{s}(k) = \bar{s}(k) + \mathbf{i}_k^H \mathbf{Q}(\mathbf{s} - \bar{\mathbf{s}}) + \mathbf{i}_k^H \mathbf{P} \mathscr{V}. \qquad (9)$$

3.2 Iterative Algorithm

We are interested in finding the a posteriori values of $\{\bar{s}(k)\}$ and $\{\mathrm{Cov}[s(k), s(k)]\}$ to use in (5) and (6). To find these values the following important steps are highlighted to apply the proposed iterative algorithm.

Step 1: Estimates $\{\hat{x}(n)\}$ are obtained using (7) and (6).

Step 2: To obtain the frequency domain estimates, $\{\hat{s}(n)\}$, the FFT is performed on samples $\{\hat{x}(n)\}$.

Step 3: In order to determine the a posteriori values of $\{\bar{s}(k)\}$ and $\{\mathrm{Cov}[s(k), s(k)]\}$ log-likelihood ratios (LLR)s of $\{\hat{s}(k)\}$ are found. The a priori and a posteriori LLR of $s(k)$ are defined as [8]

$$\begin{aligned} L[s(k)] &= ln(Pr\{s(k)=1\}/Pr\{s(k)=-1\}) \text{ and} \\ L[s(k)|_{\hat{s}(k)}] &= ln(Pr\{s(k)=1|_{\hat{s}(k)}\}/Pr\{s(k)=-1|_{\hat{s}(k)}\}). \end{aligned}$$

The difference between the a posteriori and a priori LLR of $s(k)$ is

$$\begin{aligned} \triangle L[s(k)] &= L[s(k)|_{\hat{s}(k)}] - L[s(k)] \\ &= \ln \frac{p\{\hat{s}(k)|_{s(k)=1}\}}{p\{\hat{s}(k)|_{s(k)=-1}\}} = L[\hat{s}(k)|_{s(k)}] \qquad (10) \end{aligned}$$

In order to find $L[\hat{s}(k)|_{s(k)}]$, we assume that the probability density function (PDF) of $\hat{s}(k)$ is Gaussian with variance σ_s^2 and can be written as $p\{\hat{s}(k)\} \approx \exp\left(-\frac{(\hat{s}(k)-E\{\hat{s}(k)\})(\hat{s}(k)-E\{\hat{s}(k)\})^H}{\sigma_s^2}\right)$. Therefore the conditional PDF of $\hat{s}(k)$ (when the transmitted signal $s(k) = b$) becomes $p\{\hat{s}(k)|_{s(k)=b}\} \approx \exp\left(-\frac{(\hat{s}(k)-m_k(b))(\hat{s}(k)-m_k(b))^H}{\sigma_s^2|_{s(k)=b}}\right)$. Where $m_k(b) = E\{\hat{s}(k)|_{s(k)=b}\}$ and $\sigma_s^2|_{s(k)=b} = \mathrm{Cov}[\hat{s}(k), \hat{s}(k)|_{s(k)=b}]$ are respectively the conditional mean and covariance of $\hat{s}(k)$, for a BPSK system $b = \{+1, -1\}$. Note $E\{\mathbf{s}|_{s(k)=b}\} = E\{\mathbf{s} + \mathbf{i}_k(b - s(k))\} = \bar{\mathbf{s}} + \mathbf{i}_k(b - \bar{s}(k))$, therefore from (9)

$$\begin{aligned} E\{\hat{s}(k)|_{s(k)=b}\} &= E\{\mathbf{i}_k^H \mathbf{Q}(\mathbf{s} - \mathbf{i}_k(s(k) - b) - \bar{\mathbf{s}})\} \\ &= \mathbf{Q}_{k,k} b + \bar{s}(k)(1 - \mathbf{Q}_{k,k}). \qquad (11) \end{aligned}$$

The a posteriori LLR $L[s(k)|_{\hat{s}(k)}]$, should not depend on the a priori LLR $L[s(k)]$. Therefore, we set $L[s(k)] = 0$ when finding the a posteriori LLR of $s(k)$ that yields $\bar{s}(k) = 0$ and $\mathrm{Cov}[s(k), s(k)] = 1$. Moreover, it can be noted that $m_k(b)$ depends on the particular value of b. Similarly, it can be shown that the conditional variance of $\hat{s}(k)$ becomes,

$$\begin{aligned} \sigma_s^2|_{s(k)=b} &= E\{(\hat{s}(k) - m_k(b))(\hat{s}(k) - m_k(b))^H\} \\ &= E\{(\hat{s}(k) - \mathbf{Q}_{k,k} b)(\hat{s}(k) - \mathbf{Q}_{k,k} b)^H\} \\ &= E\{\hat{s}(k)\hat{s}(k)^H|_{s(k)=b}\} - |\mathbf{Q}_{k,k}|^2 \\ &= \mathbf{i}_k^H \mathbf{Q}\, \mathrm{Cov}(\mathbf{s}, \mathbf{s}) \mathbf{Q}^H \mathbf{i}_k + \sigma^2 |\mathbf{P}_{k,k}|^2 - |\mathbf{Q}_{k,k}|^2. \end{aligned}$$

Unlike the mean the variance of the estimator is independent of b, therefore when writing variance in the sequel the conditional value is omitted. Now we have everything for $L[\hat{s}(k)|_{s(k)}]$, therefore

$$\begin{aligned} L[\hat{s}(k)|_{s(k)}] &= -\frac{(\hat{s}(k) - m_k(+1))^2}{\sigma_s^2} + \frac{(\hat{s}(k) - m_k(-1))^2}{\sigma_s^2} \\ &= 4\frac{Re\{\hat{s}(k)\mathbf{Q}_{k,k}^*\}}{\sigma_s^2} \qquad (12) \end{aligned}$$

and $L[s(k)|_{\hat{s}(k)}] = L[s(k)] + \triangle L[s(k)]$.

Step 4: Once the LLRs are obtained, the a posteriori values for $\bar{s}(k)$ and $\mathrm{Cov}[s(k), s(k)]$ are obtained as [8]

$$\begin{aligned} \bar{s}(k)|_{\hat{s}(k)} &= Pr\{s(k) = +1|_{\hat{s}(k)}\} - Pr\{s(k) = -1|_{\hat{s}(k)}\} \\ &= \tanh\left(\frac{L_{post}[s(k)]}{2}\right) \qquad (13) \\ \mathrm{Cov}[s(k), s(k)]|_{\hat{s}(k)} &= 1 - \bar{s}(k)^2. \qquad (14) \end{aligned}$$

Step 5: Performing an IFFT on the a posteriori values obtained in (13) yields the a posteriori values of $\{\bar{x}(n)\}$.

Step 6: We proceed to step 1 for the next iteration until we obtain the desired BER or the specified number of iterations has elapsed.

4. COMPLEXITY OF THE ALGORITHM

Although the size of matrix $\mathbf{H}_n$ is $L \times N$, it contains only $2L - 1$ non-zero columns. In each iteration to find the equalizer coefficient values, $\mathbf{w}_n$, the algorithm requires the computation of $(\mathbf{H}_n \mathbf{F}^H \mathrm{Cov}(\mathbf{s}, \mathbf{s}) \mathbf{F} \mathbf{H}_n^H + \sigma^2 \mathbf{I}_L)^{-1} \mathbf{H}_n \mathbf{F}^H \mathrm{Cov}(\mathbf{s}, \mathbf{s}) \mathbf{F} \mathbf{i}_n$. The computation of $\mathbf{F}^H \mathrm{Cov}(\mathbf{s}, \mathbf{s}) \mathbf{F}$ requires $N\log N$ operations and must be performed once per iteration, given $\mathbf{F}^H \mathrm{Cov}(\mathbf{s}, \mathbf{s}) \mathbf{F}$ the computation of $\mathbf{H}_n \mathbf{F}^H \mathrm{Cov}(\mathbf{s}, \mathbf{s}) \mathbf{F} \mathbf{H}_n^H$ and $\mathbf{H}_n \mathbf{F}^H \mathrm{Cov}(\mathbf{s}, \mathbf{s}) \mathbf{F} \mathbf{i}_n$ requires respectively $\mathscr{O}(L^2)$ and $\mathscr{O}(L)$ operations, and each must be performed N times per iteration. The size of the matrix $(\mathbf{H}_n \mathbf{F}^H \mathrm{Cov}(\mathbf{s}, \mathbf{s}) \mathbf{F} \mathbf{H}_n^H + \sigma^2 \mathbf{I}_L)^{-1}$ is $L \times L$ and it is Hermitian, therefore it will require $\mathscr{O}(L^2)$ operations to be performed N times per iteration. In order to estimate $\hat{x}(n)$, the computation of $\mathbf{H}_n \bar{\mathbf{x}}$ requires $\mathscr{O}(L^2)$ operations and must be performed N times per iteration. In order to find the a posteriori values of $\mathrm{Cov}[\hat{s}(k), \hat{s}(k)]$ the values of $\mathbf{Q}_{k,k}$ and $\mathbf{P}_{k,k}; k = 0, 1, ..., N-1$ are required and can be computed explicitly from the expressions for $\mathbf{Q}$ and $\mathbf{P}$ in the computations of $\mathscr{O}(LN)$ or $\mathscr{O}(N\log N)$ [9]. Hence, to estimate N symbols, we only require $(\mathscr{O}(N\log N) + \mathscr{O}(NL^2))$ operations.

5. SIMULATION

In this section, we compare the performance of our low complexity MMSE-iterative algorithm with the L-MMSE equalizer [3]. The number of sub-carriers is chosen to be $N = 32$ and the length of the cyclic prefix is equal to the order of the channel. We use a 4-tap wireless fading channel model in which each channel tap is represented by a complex Gaussian random process independently generated with the Doppler spectrum based on Jakes' model. Here, we assume $\sum_{l=0}^{L-1} \sigma_l^2 = 1$, where σ_l^2 is the variance of the lth path. The frequency domain transmitted signals, $\{s(k)\}$, are assumed to be BPSK. In order to see the benefits of employing the proposed iterative method, bit and symbol error rate performances are compared with the L-MMSE equalizer in Fig. 3 and 4. For an LTI channel, the L-MMSE equalizer yields the optimum performance. Since the channel changes very slowly for low Doppler shift, the performances for the iterative and L-MMSE equalizers are essentially identical, as can be seen from Fig. 3 and 4. But, as significant Doppler shift introduces significant time selectivity into the channel, the proposed algorithm outperforms the L-MMSE equalizer and provides time diversity gain.

6. CONCLUSIONS

We considered the design of a low complexity iterative receiver for the doubly selective environment. The simulation results support the expected superiority of the proposed iterative scheme over the L-MMSE equalization that is not only computationally expensive but has poor performance. On the other hand, unlike the iterative method proposed in [4], the computational complexity of our proposed algorithm is independent of DS and does not require any preprocessing and can work for a large range of DS without increasing the computational complexity. It also yields the time diversity benefit in LTV channels.

Acknowledgment

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REFERENCES

[1] G. L. Stuber, J. R. Barry, S. W. Mclaughlin, and M. A. Ingram, " Broadband MIMO-OFDM wireless communs.," *Proc. IEEE*, vol. 92, pp. 271 – 294, Feb. 2004.

[2] X. Cai and G. B. Giannakis, " Low-complexity ICI suppression for OFDM over time and frequency-selective Rayleigh fading channels ," *Asilomar Conference on Signals, Systems and Computers*, vol. 2, pp. 1822 – 1826, Nov 2002.

[3] Y. S. Choi, P. J. Voltz, and F. A. Cassara, "On channel estimation and detection for multi-carrier signals in fast and selective Rayleigh fading channels ," *IEEE Trans. Communs*, vol. 49, pp. 1375 – 1387, Aug 2001.

[4] P. Schniter, "Low-complexity equalization of OFDM in doubly selective channels," *IEEE Trans. on Signal Processing*, vol. 52, pp. 1002–1010, April 2004.

[5] J. Zhang, W. Ser, and J. S. Zhu, "Effective optimisation method for channel shortening in OFDM systems," *IEE Communs. Proceedings*, vol. 52, pp. 85–90, Apr. 2003.

[6] S. Ahmed, S. Lambotharan, A. Jakobsson, and J. A. Chambers, "Parameter estimation and equalization techniques for communication channels with multipath and multiple frequency offsets," *IEEE Trans. Communs.*, vol. 53, pp. 219–223, Feb. 2005.

[7] T. Kailath, *Linear Estimation*. Upper Saddle River, N.J.: Prentice Hall, 2000.

[8] M. Tüchler, R. Koetter, and A. C. Singer, "Turbo equalization: Principles and new results," *IEEE Trans. Commun.*, vol. 50, pp. 754–766, May. 2002.

[9] S. Ahmed, M. Sellathurai, and J. A. Chambers, "Low complexity iterative methods of equalization for time varying channels in OFDM," *IEEE Trans. Signal Processing*, To be Submitted.

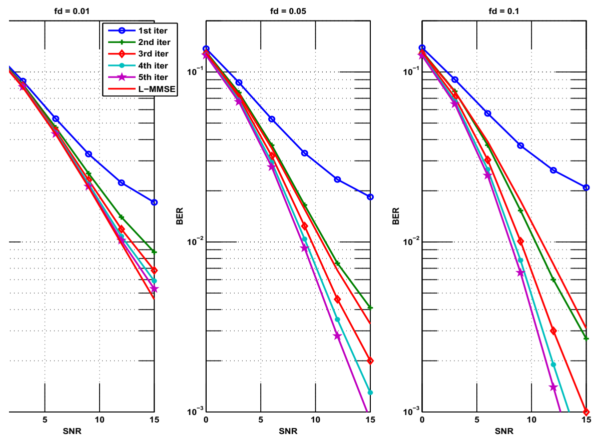

Figure 3: Comparison of BER performance of MMSE-iterative algorithm with the L-MMSE equalizer up to five iterations and at different DS.

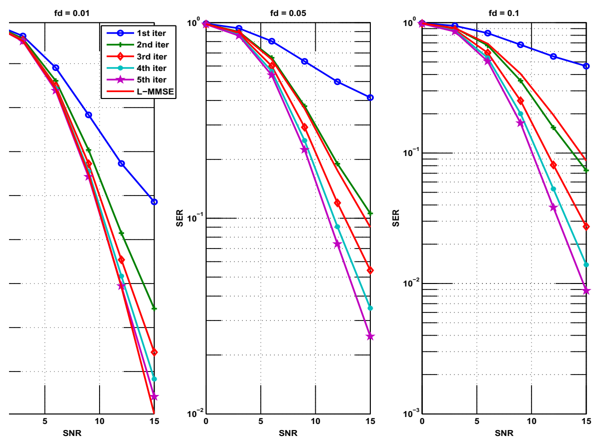

Figure 4: Comparison of symbol error rate (SER) performance of MMSE-iterative algorithm with the L-MMSE equalizer up to five iterations and at different DS.