

Low Complexity Joint Semiblind Detection for OFDM Systems over Time-Varying Channels

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Abstract—Orthogonal frequency division multiplexing (OFDM) modulation is widely used in communication systems to meet the demand for ever increasing data rates. In this paper, a low complexity joint semiblind detection algorithm for OFDM systems over time-varying channels is proposed based on the channel correlation and noise variance. The problem is relaxed to a continuous non-convex quadratic programming problem. Then an iterative method is utilized to deduce a sequence of reduced-size quadratic programming problems. These are solved by limiting the search in the 2-dimensional subspace. Furthermore, a low-bit descent search is employed to improve the system performance. Results are given which demonstrate that the proposed algorithm provides comparable performance with lower computational complexity than that of a sphere decoder.

I. INTRODUCTION

Orthogonal frequency division multiplexing (OFDM) modulation is widely used in communication systems to efficiently provide high data rates. The major advantage of OFDM over single-carrier transmission is its ability to deal with severe channel conditions without complex equalization. The standards employing OFDM modulation include digital video broadcasting (DVB) [1], digital audio broadcasting DAB [2], IEEE 802.11 [3] for wireless local area networks, and IEEE 802.16 [4] for wireless metropolitan area networks.

In an OFDM system, the data stream is modulated on orthogonal subcarriers using phase-shift keying (PSK) or quadrature amplitude modulation (QAM). OFDM systems are sensitive to Doppler spread caused by user mobility, which results in loss of orthogonality among subcarriers. This leads to intercarrier interference (ICI) which degrades system performance.

In the design of most ICI reduction algorithms for OFDM systems [5]-[6], perfect channel information is assumed at the receiver. Many channel estimation methods have been proposed for OFDM systems based on pilot symbols [7] [8]. In most cases, channel estimation with pilot symbols is a robust method. However, there are disadvantages such as bandwidth loss and overhead, which can be excessive in fast fading channels. This motivates the use of joint blind or semiblind detection methods for OFDM systems. These methods exploit the statistical or deterministic properties of the channel to detect the transmitted signals without estimating the channel [9]-[11].

There have been several recent investigations on the joint channel estimation and data detection problem in communication systems. In [9], a joint maximum-likelihood (ML) channel estimation and signal detection problem for single-input multiple-output (SIMO) systems was formulated and solved via sphere decoding. A blind joint detection problem was formulated in [10] as an integer programming problem based on a regression model. Cui and Tellambura [11] proposed three ML data detectors for OFDM systems over fast fading channels with the assumption of known channel correlation.

A sphere decoder for joint semiblind detection provides near-optimal performance with low computational complexity compared to an exhaustive search [11]. However, the complexity is still high, so there is need for a suboptimal detector which yields a fast solution with good performance. In this paper, an iterative joint semiblind detection algorithm (IJSB) for OFDM systems over time-varying channels is proposed. The detection problem is first relaxed to a continuous non-convex quadratic programming (QP) problem. A sequence of reduced-size QP problems are then deduced and solved by limiting the search in the 2-dimensional subspace spanned by its steepest-descent and Newton directions to reduce the computational complexity. Furthermore, a low-bit descent search (LBDS) is employed to improve the system performance.

II. SYSTEM MODEL

Here we consider the problem of joint ML channel estimation and signal detection in an N -subcarrier OFDM system, where the channel is time-varying within one OFDM symbol duration, and the channel information is partly known, i.e., the channel correlation and noise variance.

In an OFDM system, the transmitted signal is generated using an inverse fast Fourier transform (IFFT)

$$x_n = \frac{1}{\sqrt{N}} \sum_{k=0}^{N-1} X_k \exp\left(\frac{j2\pi kn}{N}\right) \text{ for } n = 0, \dots, N-1 \quad (1)$$

where x_n is the time-domain signal at the n th sampling instant, and X_k is the frequency-domain data symbol for the k th subcarrier. Equation (1) can be written in vector form as

$$\mathbf{x} = \mathbf{F}\mathbf{X} \quad (2)$$

where $\mathbf{x} = [x_0 \ x_1 \ \dots \ x_{N-1}]^T$ and $\mathbf{X} = [X_0 \ X_1 \ \dots \ X_{N-1}]^T$ represent the time-domain and frequency-domain OFDM symbols, respectively, and $(\cdot)^T$ denotes transpose of a vector or matrix. \mathbf{F} is the IFFT matrix with elements $f_{n,k} = \frac{1}{\sqrt{N}} \exp(j\frac{2\pi kn}{N})$. The OFDM symbol duration is denoted by T_s , so the chip duration of each subchannel is $T_c = T_s/N$.

In this paper, we consider a doubly selective fading channel model [12]. Thus, we have a wide sense stationary uncorrelated scattering (WSSUS) channel with impulse response given by

$$h(t; \tau) = \sum_{l=0}^{L-1} h(t; \tau_l) \delta(\tau - \tau_l) \quad (3)$$

where τ_l is the l th path delay with $\tau_0 < \tau_1 < \dots < \tau_{L-1}$, and $h(t; \tau_l)$ is a complex Gaussian process with zero mean and variance σ_l^2 . In a rich scattering environment, the channel autocorrelation function is separable in terms of time and delay [12], where the time-correlation function of the channel is characterized based on Jakes' model [13] as

$$E\{h_{l_1}(t + \Delta t) h_{l_2}^*(t)\} = \sigma_l^2 r_t(\Delta t) \delta(l_1 - l_2) \quad (4)$$

where $r_t(\Delta t) = J_0(2\pi f_d \Delta t)$, and $J_0(\cdot)$ denotes the zeroth-order Bessel function of the first kind. The frequency-domain correlation of the channel is given by

$$r_f(\Delta f) = \sum_{l=0}^{L-1} \sigma_l^2 e^{-j2\pi \Delta f \tau_l} \quad (5)$$

For simplicity, we assume $\tau_l = lT_c$.

Generally a cyclic prefix (CP) is inserted at the beginning of each OFDM symbol before transmission. The length N_{cp} of the cyclic prefix is greater than or equal to that of the channel impulse response to eliminate intersymbol interference. Consequently, the discrete signal at the receiver can be expressed as

$$y_n = \sum_{l=0}^{L-1} h(n, l) x(n-l) + w_n \quad \text{for } n = -N_{cp}, \dots, N-1 \quad (6)$$

where w_n is additive white Gaussian noise (AWGN) with zero mean and variance σ^2 .

After removing the CP and performing a fast Fourier transform (FFT), we obtain

$$\mathbf{Y} = \mathbf{A}\mathbf{X} + \mathbf{W} \quad (7)$$

where $\mathbf{Y} = [Y_0 \ \dots \ Y_{N-1}]^T$ is the frequency-domain received signal, $\mathbf{A} = \mathbf{F}^H \mathbf{H} \mathbf{F}$, $\mathbf{W} = \mathbf{F}^H \mathbf{w}$, and $(\cdot)^H$ denotes conjugate transpose of a vector or matrix. \mathbf{H} and \mathbf{w} denote the time-domain channel matrix and AWGN noise, respectively,

If $h(t; \tau_l)$ in (3) remains constant within one OFDM symbol duration, then \mathbf{A} is a diagonal matrix, and no ICI will occur. Conversely, if the channel varies within one OFDM symbol, the orthogonality of the subcarriers does not hold, and the received signal contains both the transmitted signal and ICI

from other subcarriers [7]. In this case, the received signal on the k th subcarrier is

$$Y_k = A_{k,k} X_k + \sum_{m=0, m \neq k}^{N-1} A_{k,m} X_m + W_k \quad (8)$$

where $k = 0, \dots, N-1$, $A_{k,m}$ denotes the (k, m) th element of \mathbf{A} and $\sum_{m=0, m \neq k}^{N-1} A_{k,m} X_m$ represents the ICI caused by other subcarriers.

According to the central limit theorem, the received signal \mathbf{Y} can be modeled as i.i.d. zero mean complex Gaussian random variables. Thus, the autocorrelation matrix of \mathbf{Y} in (7) can be written as [11]

$$\mathbf{R}_{\mathbf{Y}\mathbf{Y}} = \sigma_{ICI}^2 (\mathbf{X}_D \mathbf{R}_f \mathbf{X}_D^H + \sigma_{en}^2 \mathbf{I}_N) \quad (9)$$

where $\mathbf{X}_D = \text{diag}(\mathbf{X})$

$$[\mathbf{R}_f]_{(i,j)} = r_f((i-j)/NT_c) \quad (10)$$

$$\sigma_{ICI}^2 = \frac{1}{N^2} \sum_{n_1=0}^{N-1} \sum_{n_2=0}^{N-1} r_t[(n_1 - n_2)T_c] \quad (11)$$

and

$$\sigma_{en}^2 = \frac{((\sum_{l=0}^{L-1} \sigma_l^2)(1 - \sigma_{ICI}^2) + \sigma^2)}{\sigma_{ICI}^2} \quad (12)$$

III. JOINT SEMIBLIND DETECTION PROBLEM FORMULATION

The correlation within the received signal is utilized to develop the semiblind joint detector for OFDM systems in the frequency-domain. By maximizing the log-likelihood function of the received signal conditioned on the transmitted signal, joint semiblind detection can be formulated as the following minimization problem

$$\text{minimize } \mathbf{Y}^H \mathbf{R}_{\mathbf{Y}\mathbf{Y}}^{-1} \mathbf{Y} \quad (13a)$$

$$\text{subject to: } X_k \in \mathcal{M} \quad \text{for } k = 0, \dots, N-1 \quad (13b)$$

where \mathcal{M} contains the symbols from the modulation used.

Assuming BPSK or QPSK modulation, we have $|X_k| = 1$. Thus the minimization problem (13) is equivalent to the problem [11]

$$\text{minimize } \mathbf{X}^T \mathbf{Y}_D^H \{\sigma_{ICI}^2 (\mathbf{R}_f + \sigma_{en}^2 \mathbf{I}_N)\}^{-1} \mathbf{Y}_D \mathbf{X}^* \quad (14a)$$

$$\text{subject to: } X_k \in \mathcal{M} \quad \text{for } k = 0, \dots, N-1 \quad (14b)$$

where \mathbf{X}^* denotes the conjugate of the transmitted signal \mathbf{X} . Note that this semiblind detector exhibits a phase ambiguity, where $\mathbf{X} e^{j\phi}$, $\phi \in [0, 2\pi)$, satisfies (14). One or more pilot tones can be employed to compensate for this ambiguity.

Define $\hat{\mathbf{Q}} = \mathbf{Y}_D^H \{\sigma_{ICI}^2 (\mathbf{R}_f + \sigma_{en}^2 \mathbf{I}_N)\}^{-1} \mathbf{Y}_D$, it can be seen that $\hat{\mathbf{Q}}$ is a positive definite Hermitian matrix. However, the computational effort required to solve the semiblind problem (14) increases exponentially with the number of variables. In [11], a sphere decoder was proposed to solve this problem and

provide near-optimal performance. Although the computational complexity of the sphere decoder is reduced by examining lattice points inside a hypersphere [14], we seek a suboptimal detector which provides comparable results to that of the sphere decoder with lower computational complexity.

For simplicity, only the algorithm for a QPSK OFDM system is described, as the algorithm for BPSK can be obtained with a straightforward modification. As (14) is a complex-valued optimization problem, we convert it into the following real-valued optimization problem

$$\text{minimize } \|\mathbf{M}\mathbf{z}\| \quad (15a)$$

$$\text{subject to: } z_k \in \left\{-\frac{\sqrt{2}}{2}, \frac{\sqrt{2}}{2}\right\} \text{ for } k = 0, \dots, 2N - 1 \quad (15b)$$

$$\text{where } \mathbf{M} = \begin{bmatrix} \text{real}(\hat{\mathbf{M}}) & \text{imag}(\hat{\mathbf{M}}) \\ \text{imag}(\hat{\mathbf{M}}) & -\text{real}(\hat{\mathbf{M}}) \end{bmatrix}, \hat{\mathbf{Q}} = \hat{\mathbf{M}}^H \hat{\mathbf{M}}, \text{ and } \mathbf{z} = \begin{bmatrix} \text{real}(\mathbf{X}) \\ \text{imag}(\mathbf{X}) \end{bmatrix}.$$

Clearly, the above problem is equivalent to a quadratic programming problem of the form

$$\text{minimize } \mathbf{z}^T \mathbf{Q} \mathbf{z} \quad (16a)$$

$$\text{subject to: } z_k \in \{-1, 1\} \text{ for } k = 0, \dots, 2N - 1 \quad (16b)$$

where $\mathbf{Q} = \mathbf{M}^T \mathbf{M}$.

Problem (16) is a combinatorial optimization problem with exponential computational complexity. This type of ML detection problem can be solved more efficiently by expanding the discrete feasible set into a continuous feasible region. The constraints in (16b) imply $\mathbf{z}^T \mathbf{z} = 2N$, which corresponds to a $2N$ -dimensional sphere centered at the origin with radius $\sqrt{2N}$. Thus problem (16) can be converted to

$$\min \mathbf{z}^T \mathbf{Q} \mathbf{z} \quad (17a)$$

$$\text{subject to: } \mathbf{z}^T \mathbf{z} = 2N \quad (17b)$$

The receiver has knowledge that a particular QPSK symbol was transmitted on some pre-defined subcarriers, and this can be utilized to solve problem (17). Let \mathbf{z}_d be the vector of the unknown transmitted data, Ω_d be the index set corresponding to \mathbf{z}_d , and N_d be the size of \mathbf{z}_d . The corresponding pilot symbol vector is denoted as \mathbf{z}_p , Ω_p is the index set associated with \mathbf{z}_p , and N_p is the size of \mathbf{z}_p . By substituting the known pilot tones \mathbf{z}_p from the variable vector \mathbf{z} , \mathbf{Q}_d and \mathbf{q}_d can be obtained from \mathbf{Q} with respect to Ω_d and Ω_p , respectively. Consequently we have a quadratic optimization problem of the form

$$\text{minimize } \mathbf{z}_d^T \mathbf{Q}_d \mathbf{z}_d + \mathbf{q}_d^T \mathbf{z}_d \quad (18a)$$

$$\text{subject to: } \mathbf{z}_d^T \mathbf{z}_d = N_d \quad (18b)$$

IV. AN ITERATIVE JOINT SEMIBLIND DETECTION ALGORITHM

A. Basic algorithm

The variables in (18) can be iteratively detected, where only some binary components of \mathbf{z}_d are determined in each iteration by solving a corresponding non-combinatorial problem of type (18). Suppose that prior to the i th iteration some binary components of vector \mathbf{z}_d have been determined. Let \mathbf{z}_i be the reduced-size vector that collects all undecided components of \mathbf{z}_d , Ω_i be the index set corresponding to \mathbf{z}_i , and N_i be the size of \mathbf{z}_i during the i th iteration, respectively. By substituting the known binary components of \mathbf{z}_d into (18), a reduced-size problem similar to (18) is obtained as

$$\text{minimize } \mathbf{z}_i^T \mathbf{Q}_i \mathbf{z}_i + \mathbf{q}_i^T \mathbf{z}_i \quad (19a)$$

$$\text{subject to: } \mathbf{z}_i^T \mathbf{z}_i = N_i \quad (19b)$$

The computational complexity is reduced by realizing that the variable set in problem (19) can be expressed with respect to a 2-dimensional subspace spanned by its steepest-descent direction (i.e., negative gradient of the objective function) and Newton direction. In doing so, we set

$$\mathbf{z}_i = \eta_1^{(i)} \mathbf{v}_1^{(i)} + \eta_2^{(i)} \mathbf{v}_2^{(i)} \quad (20)$$

where $\mathbf{v}_1^{(i)} = \mathbf{q}_i$, $\mathbf{v}_2^{(i)} = \mathbf{Q}_i^{-1} \mathbf{q}_i$, and $\eta_1^{(i)}$, $\eta_2^{(i)}$ are two scalar variables. Then (19) is converted to a 2-dimensional problem

$$\text{minimize } \boldsymbol{\eta}_i^T \mathbf{S}_i \boldsymbol{\eta}_i + \mathbf{p}_i^T \boldsymbol{\eta}_i \quad (21a)$$

$$\text{subject to: } \boldsymbol{\eta}_i^T \mathbf{R}_i \boldsymbol{\eta}_i = N_i \quad (21b)$$

where $\boldsymbol{\eta}_i = [\eta_1^{(i)} \ \eta_2^{(i)}]^T$, $\mathbf{S}_i = \mathbf{V}_i^T \mathbf{Q}_i \mathbf{V}_i$, $\mathbf{p}_i = \mathbf{V}_i^T \mathbf{q}_i$, $\mathbf{R}_i = \mathbf{V}_i^T \mathbf{V}_i$, and $\mathbf{V}_i = [\mathbf{v}_1^{(i)} \ \mathbf{v}_2^{(i)}]$. Consequently, the solution of (21) must satisfy the Karush-Kuhn-Tucker (KKT) conditions

$$2\mathbf{S}_i \boldsymbol{\eta}_i + \mathbf{p}_i + 2\lambda_i \mathbf{R}_i \boldsymbol{\eta}_i = 0 \quad (22a)$$

$$\boldsymbol{\eta}_i^T \mathbf{R}_i \boldsymbol{\eta}_i = N_i \quad (22b)$$

where λ_i is a Lagrange multiplier at the i th iteration. It follows that the optimal $\boldsymbol{\eta}_i$ can be obtained from (22a) as

$$\boldsymbol{\eta}_i^* = -\frac{1}{2} (\mathbf{S}_i + \lambda_i^* \mathbf{R}_i)^{-1} \mathbf{p}_i \quad (23)$$

Thus, (22b) can be rewritten as

$$g(\lambda_i) = \sum_{k=0}^{N_i-1} \frac{\hat{p}_k^2}{(\lambda_i + s_k)^2} = 4N_i \quad (24)$$

where s_k is the k th eigenvalue of $\hat{\mathbf{S}}_i = \mathbf{R}_i^{-\frac{1}{2}} \mathbf{S}_i \mathbf{R}_i^{-\frac{1}{2}}$, which admits an eigen-decomposition $\hat{\mathbf{S}}_i = \mathbf{U}_i \boldsymbol{\Sigma}_i \mathbf{U}_i^T$, and \hat{p}_k is the k th component of vector $\hat{\mathbf{p}}_i = \mathbf{U}_i^T \mathbf{R}_i^{-\frac{1}{2}} \mathbf{p}_i$.

The only unknown variable λ_i can be determined by solving the one-variable optimization problem

$$\text{minimize } \left| \sum_{k=0}^{N_i-1} \frac{\hat{p}_k^2}{(\lambda_i + s_k)^2} - 4N_i \right| \quad (25a)$$

$$\text{subject to: } -s_l \leq \lambda_i \leq \frac{\|\hat{\mathbf{p}}_i\|}{1.5\sqrt{4N_i}} - s_l \quad (25b)$$

with s_l being the smallest value of s_k such that $\hat{p}_l \neq 0$. The unique solution λ_i^* of (25) can be effectively identified via bisection search.

Next, the magnitudes of the components of \mathbf{z}_i^* are examined. If $|z_k^*|$ exceeds a given threshold $\rho = \alpha|z_i^*|_{max}$, the corresponding variable is claimed as $\text{sign}(z_k^*)$, otherwise component z_k^* remains undetermined and will be considered as a design variable in the next iteration. Based on the components just detected, a QP problem similar to (18) with reduced size is produced where the vector \mathbf{z}_i contains only the undetermined variables. This iterative process continues until all the variables have been identified to produce an estimate of the transmitted data.

Note that the evaluation of \mathbf{Q}_i^{-1} is numerically intensive when its size is large. This can be alleviated using the well-known formula for inverting a four-block matrix [15]. Thus the major portion of the computational complexity for the proposed algorithm is on the order of $O(kN^2)$ for each iteration, where k denotes the average number of variables detected in one iteration and $k \ll N$ for a typical threshold value.

B. Performance Enhancement by Low-Bit Descent Search

In LBDS, a given binary sequence is associated with an objective function to be minimized. The search process evaluates, compares, and determines the optimal sign switches of a relatively small number of sequence components to yield maximum reduction in the objective function in (18). LBDS has been applied recently to various problems [16]. As will be demonstrated by simulation, the performance of the proposed algorithm can be considerably enhanced using 1-bit or 2-bit, or a combined 1-bit-and-2-bit LBDS, at an insignificant extra cost in computational complexity.

The iteration of LBDS is described as follows [16]. At each iteration, one-bit descent search evaluates $\mathbf{z}_d \odot \boldsymbol{\xi}$ (here \odot denotes component-wise multiplication), where \mathbf{z}_d is the vector defined in Section III, $\boldsymbol{\xi} = \tilde{\mathbf{Q}}\mathbf{z}_d + \mathbf{q}_d/2$, and $\tilde{\mathbf{Q}}$ is generated from matrix \mathbf{Q}_d with its diagonal components set to zero. Index k^* is then identified as where the corresponding component ξ_{k^*} has maximum value, and the sign of z_{k^*} is switched to obtain an improved solution. Similarly, a 2-bit LBDS is performed by computing matrix $\mathbf{G} = \boldsymbol{\xi}\mathbf{e}^T + \mathbf{e}^T\boldsymbol{\xi} - 2\mathbf{Q}_d \odot (\mathbf{z}_d\mathbf{z}_d^T)$, where \mathbf{e} is the all-one vector. The index (k^*, m^*) is identified as where the component G_{k^*, m^*} reaches its maximum value, and an improved solution is then obtained by switching the signs of the k^* th and m^* th components of \mathbf{z}_d^* . The iterations continue

until there is no further reduction in the objective function (18), at which point an estimate of the transmitted data is obtained.

V. SIMULATION RESULTS

The proposed IJSD algorithm was applied to an OFDM system with $N = 64$ subcarriers and a cyclic prefix of length $N_{cp} = N/8$. The carrier frequency of the OFDM system was 5GHz and the bandwidth of the system was set to 3MHz. The 6-ray COST 207 TU model with power profile [0.189, 0.379, 0.239, 0.095, 0.061, 0.037] and delay profile [0.0, 0.2, 0.5, 1.6, 2.3, 5.0] μs was employed for the simulation. Each path is an independent complex Gaussian random process with Jake's Doppler spectrum. One or more pilot tones was utilized to compensate for the phase ambiguity, and BPSK or QPSK modulation was used for both the data and pilot symbols. The channel correlation matrix was assumed perfectly known at the receiver. The normalized Doppler frequency of the channel denoted as f_dT_s . The performance of the proposed joint detection algorithm was evaluated based on bit error rate (BER) and computational complexity, in comparison with a sphere decoder. The performance of the recursive detector [6] was used as the benchmark with the assumption of perfect channel state information (CSI).

The BER performance was evaluated with $f_dT_s = 0.01$ for both BPSK and QPSK OFDM systems, as shown in Figs. 1 and 2. It can be observed that the IJSD algorithm provides comparable results to those of the sphere decoder with much less computational complexity. For example, for the QPSK OFDM system, at an E_b/N_0 of 30dB, the sphere algorithm has a BER of 6.4×10^{-4} , while the proposed algorithm with $\alpha = 0.8$ achieves a BER of 3×10^{-3} (with only 55% of the CPU time of the sphere decoder). This is improved to a BER of 8.5×10^{-4} with LBDS (and 57% of the CPU time of the sphere decoder).

A larger α can provide better performance at a cost of increased computational complexity, as shown in Fig. 3. The proposed algorithm exhibits a performance loss due to a smaller threshold, but this loss can be avoided by performing LBDS with a slightly increased computational complexity. For the QPSK OFDM system with Doppler spread $f_dT_s = 0.01$, the algorithm with $\alpha = 0.5$ only requires 45% of the CPU time of the sphere decoder at an E_b/N_0 of 30dB. The corresponding BER with $\alpha = 0.5$ is 4.5×10^{-3} . This can be improved to 9×10^{-4} by performing LBDS with 50% of the CPU time of the sphere decoder. Table I summarizes the computational complexity of the IJSD algorithm relative to that of the sphere decoder for a QPSK OFDM system at $E_b/N_0 = 30\text{dB}$, where the CPU time of the sphere decoder is normalized to one.

Simulations were also carried out to determine the impact of normalized doppler spread f_dT_s on the system performance. The BER performances of the proposed algorithm for $f_dT_s = 0.001, 0.005, \text{ and } 0.01$ are depicted in Fig. 4. It can be observed that at lower SNR, the proposed algorithm provides similar performance for all values of Doppler spread. However,

for smaller Doppler spreads, better performance was achieved at higher SNRs, e.g., at $E_b/N_0 = 30\text{dB}$, a BER of 8.5×10^{-4} was obtained for $f_d T_s = 0.01$ using the proposed algorithm with LBDS, while a BER of 2.5×10^{-4} can be achieved for $f_d T_s = 0.001$.

Simulations were also carried out to determine the impact of the number of pilot tones on performance. The BER of the proposed algorithm with LBDS for $f_d T_s = 0.01$ and 1, 2 and 4 pilot tones is shown in Fig. 5. It can be observed that there is an error floor at high signal-to-noise ratios with one pilot tone. The performance improves as the number of the pilot tones increases, with the error floor significantly reduced. For example, with one pilot tone, the proposed algorithm with LBDS achieves a BER of 0.015 at a E_b/N_0 of 30dB, while with 2 pilot tones, a BER of 2.2×10^{-3} is obtained for the same E_b/N_0 . The performance can be further improved to a BER of 8.5×10^{-4} by utilizing 4 pilot tones.

VI. CONCLUSIONS

A low complexity joint semiblind detection algorithm for OFDM systems over time-varying channels has been proposed. The joint semiblind problem was relaxed to a continuous non-convex QP problem. An iterative method was then utilized to deduce a sequence of reduced-size QP problems by taking advantage of the pilot tones. These were solved by limiting the search in the 2-dimensional subspace to reduce the computational complexity. Furthermore, a low-bit descent search was employed to improve the system performance. Results were given which demonstrated that the proposed algorithm provides similar performance with lower computational complexity compared to that of a sphere decoder.

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TABLE I
COMPUTATIONAL COMPLEXITY COMPARISON

Algorithm	Normalized CPU time	
	$\alpha = 0.8$	$\alpha = 0.5$
IJSD Without LBDS	0.55	0.45
IJSD With LBDS	0.57	0.5
Sphere decoder	1	

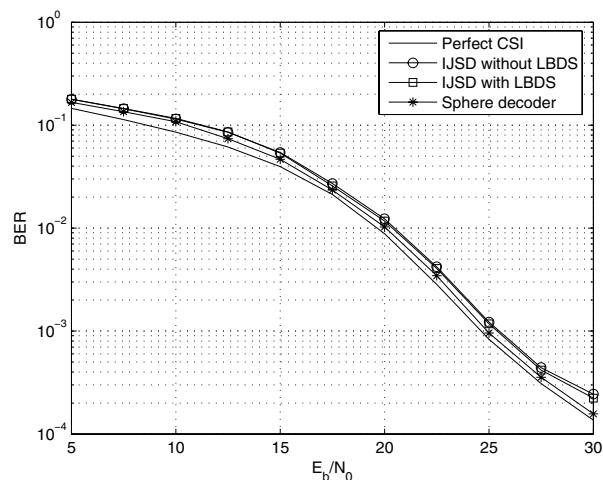


Fig. 1. BPSK OFDM system performance with $f_d T_s = 0.01$, $\alpha = 0.8$ and 4 pilot tones.

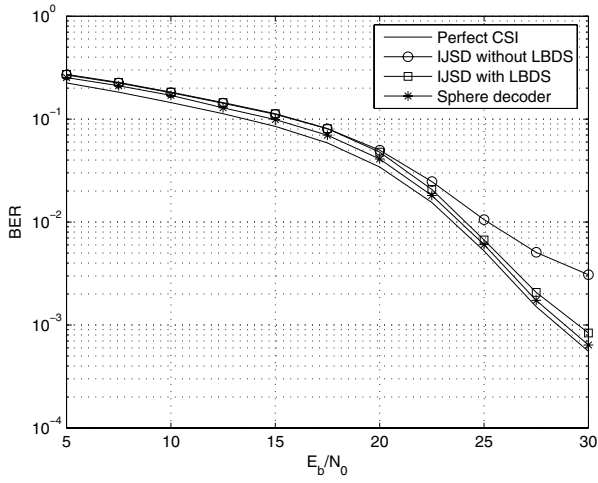


Fig. 2. QPSK OFDM system performance with $f_d T_s = 0.01$, $\alpha = 0.8$ and 4 pilot tones.

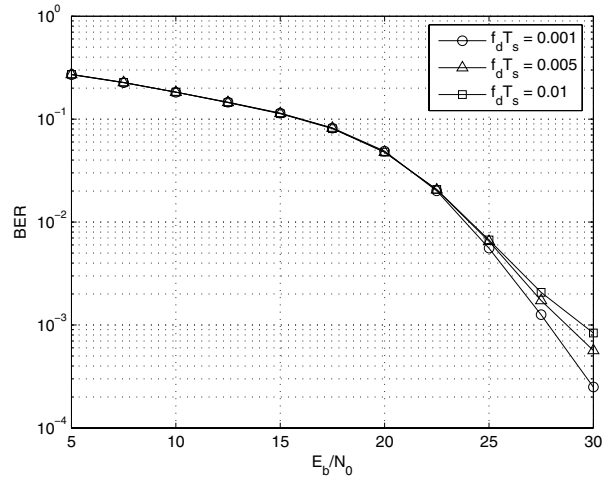


Fig. 4. QPSK OFDM system performance with $\alpha = 0.8$, 4 pilot tones and various Doppler spreads using the proposed IJSD algorithm with LBDS.

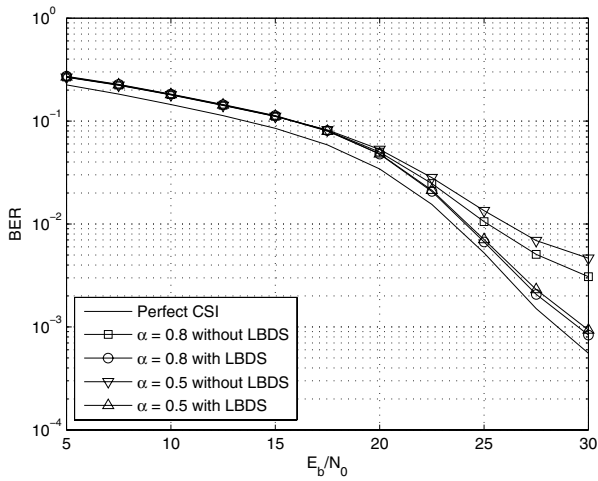


Fig. 3. QPSK OFDM system performance with $f_d T_s = 0.01$, 4 pilot tones and various thresholds using the proposed IJSD algorithm.

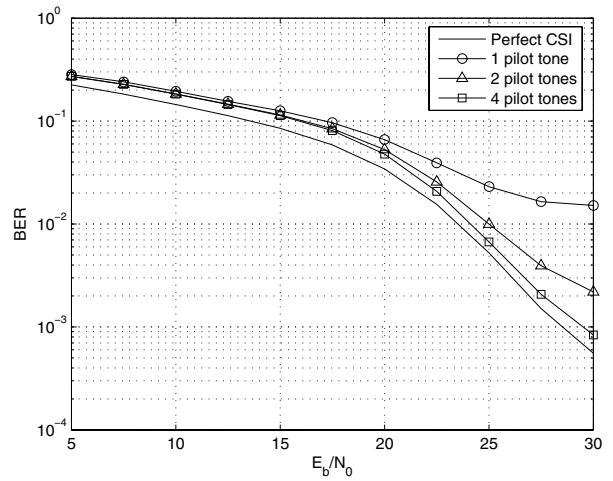


Fig. 5. QPSK OFDM system performance with $f_d T_s = 0.01$, $\alpha = 0.8$ and various pilot tones using the proposed IJSD algorithm with LBDS.