Iterative Channel Estimation for IDMA Systems in Time-Varying Channels

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Abstract— **In this paper, we develop low-complexity iterative channel estimation techniques for emerging IDMA systems. The channel estimators make use of pilots as well as soft decoded data information. We derive a lower bound for channel estimation error that reflects the reliability of soft decoded data. We show that the estimators perform close to a minimum variance unbiased estimator as the mean square error (MSE) approaches the lower bound. Numerical results on the MSE and BER performance also show that the proposed channel estimators are able to track the time-varying channel states.**

I. Introduction

Recently, a spread-spectrum multiple access scheme named interleave-division multiple-access (IDMA) has been proposed [1] [2]. Unlike code-division multiple-access (CDMA) which uses orthogonal or near-orthogonal spreading sequences to achieve bandwidth expansion and user separation, IDMA devotes the entire bandwidth expansion to low-rate channel FEC coding. Each user in an IDMA system is assigned a unique interleaver to separate user transmissions. Recent studies have shown that low-rate coded IDMA approaches the multiple access channel capacity even with equal power allocation [3]. Furthermore IDMA is able to reach the channel capacity [4] and maximum spatial efficiency [5] if optimal power allocation scheme is applied.

Low-complexity iterative multiuser detection (MUD) has been extensively studied since the advent of turbo codes. This detection approach has been applied to CDMA [6], trellis-code multiple-access (TCMA) [7] and to IDMA as well [1] [2]. For coded IDMA systems, an iterative partial decoding scheme is proposed to further reduce the receiver complexity and still guarantee fast decoding convergence [8].

For a coherent receiver, robust channel estimation is crucial for detection. In IDMA, channel estimation is performed at chip level where the signal-to-noise ratio (SNR) is very low. This challenging situation requires sophisticated channel estimation. On the other hand, the complexity of the channel estimator needs to be kept low in an iterative receiver. Pilot-aided channel estimation is first studied in [9], where the pilot sequence is superimposed on the data sequence to allow channel estimation and detection to be done at the same time instant. Therefore, this approach can be adopted in fast fading channels. For pilot-aided channel estimation, semi-blind techniques are studied to improve performance over blind channel estimation techniques. Choi proposes a method that combines pilots and traffic channel information to perform channel estimation in CDMA [10]. Schoeneich and Hoeher develop semiblind channel estimation methods for IDMA systems that outperform training-based estimation [11] [12]. However, the computational complexity of their methods is high due to the inverse performed on matrices of long blocks of chips. In this paper, we develop two low-complexity channel estimation algorithms which are based on the least square (LS) approach and the maximal ratio combining (MRC) approach respectively. Both methods use pilots as well as decoded data to perform iterative channel estimation for multipath fading channels. In particular, the MRC method weighs channel estimates from pilot and data decoding information w.r.t. their respective reliability to generate a new estimate in an optimal way. We analyze the mean square error (MSE) of the estimated parameters using a modified lower bound that is adaptive to the soft decoding information.

The rest of this paper is organized as follows. In Section II the IDMA transmitter and receiver structure are presented. In Section III low-complexity channel estimation methods are derived and their MSE performances are analyzed. In Section IV the iterative MUD is outlined. In Section V simulation results are reported. Finally, conclusions are drawn in Section VI.

II. IDMA system model

We consider an asynchronous IDMA system with K users transmitting with equal power over a multipath fading channel using QPSK modulation for simplicity, i.e. a single data layer as the in-phase component and a single pilot layer as the quadrature component. Note that our channel estimation methods can be directly applied to multilayer IDMA systems as well.

A. Transmitter Structure

Fig. 1(a) shows the transmitter structure of an IDMA system for user k. The input bit sequence b_k of user k is encoded using a low-rate code, producing a coded sequence $c_k = \{c_k[1], ..., c_k[m], ..., c_k[M]\}$, where M is the length of the data frame. The coded sequence c_k is then permutated by an interleaver to generate the transmitted data sequence $d_k = \{d_k[1], ..., d_k[m], ..., d_k[M]\}$. A pilot sequence $p_k = \{p_k[1], ..., p_k[m], ..., p_k[M]\}$ is generated separately. Finally d_k and p_k are in-phase and quadrature modulated respectively,

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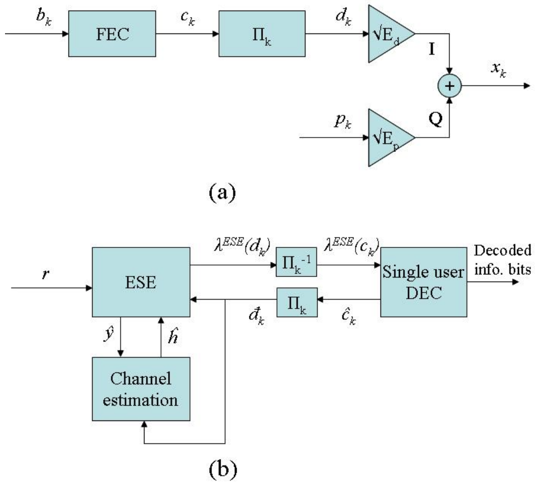

Fig. 1. IDMA transmitter and receiver structure

and multiplexed together to form transmitted signals x_k, given by

$$x_k[m] = \sqrt{E_d} d_k[m] + \sqrt{E_p} p_k[m] \tag{1}$$

where E_d and E_p are the transmitting powers for data and pilots.

B. Receiver Structure

We use a tapped delay line to model the multipath channel. Each tap varies independently. Perfect timing is assumed. After chip-matched filtering, the received signal can be modelled as

$$\begin{aligned} r[m] &= \sum_{k=1}^{K} \sum_{l=0}^{L} h_{k,l}[m] x_k[m-\tau_l] + n[m] \\ &= \sum_{k=1}^{K} \sum_{l=0}^{L} h_{k,l}[m] (\sqrt{E_d} d_k[m-\tau_l] \\ &\quad + \sqrt{E_p} p_k[m-\tau_l]) + n[m] \end{aligned} \tag{2}$$

where $h_{k,l}$ is the channel gain of the lth path for user k, τ_l represents the delay in lth path, and n is the complex Gaussian noise with variance N_0.

We consider an iterative sub-optimal receiver structure shown in Fig. 1(b). At each decoding iteration, the multiple access interference (MAI) and inter-symbol interference (ISI) are firstly cancelled in the elementary signal estimator (ESE). The partial signal of lth path for user k after interference cancellation is given by

$$\begin{aligned} \hat{y}_{k,l}[m] &= r[m] - \sum_{j \neq k} \sum_{l=0}^{L} \tilde{y}_{j,l}[m] - \sum_{i \neq l} \tilde{y}_{k,i}[m] \\ &= h_{k,l}[m] (\sqrt{E_d} d_k[m-\tau_l] + \sqrt{E_p} p_k[m-\tau_l]) + I[m] \end{aligned} \tag{3}$$

where $\tilde{y}_{j,l}$ is the estimated signal transmitted through lth path from user j, and I denotes the residual error after interference cancellation. In the first decoding iteration, only the pilots are used to estimate the transmitted signals.

The signals after interference cancellation are passed into the channel estimation module. The channel estimator updates the estimated channel coefficients of each path for every user, which are feedback to the ESE. The ESE then focuses on the multiple access constraints, producing extrinsic log-likelihood ratios (LLRs) λ^{ESE} of the transmitted data sequence for each user. Finally a bank of K single-user decoders (DECs) perform standard a posteriori probability (APP) decoding using the ESE outputs, and generate extrinsic LLRs of the transmitted data. The output LLRs from the DECs produce soft decoded data, denoted as $\tilde{d}$, which are feedback to the channel estimator and ESE for the next iteration.

III. Channel Estimation

The channel state information (CSI) is required in MAI/ISI reconstruction and LLR computation at every decoding iteration. The accuracy of the channel estimates is therefore crucial to the effectiveness of the iterative receiver performance. In this section we present two channel estimation algorithms based on pilots and soft decoded data. The first method is similar to the semiblind joint least-square channel estimation method (JLSCE) in [12], but has much lower computational complexity as it does not require matrix inverse. We also normalize the least square estimator to obtain an unbiased estimator. The second method performs channel estimation using pilots and soft decoded data separately, and uses maximal ratio combining approach to obtain improved channel estimates. In the first iteration where no soft decoded data are available, we only use the pilots to perform the channel estimation.

A. Least Square (LS) Channel Estimator

The preliminary LS channel estimator is given by

$$\begin{aligned} \hat{h}_{k,l,m}^{LS}[m] &= \frac{1}{\sqrt{E_d}\tilde{d}_k[m-\tau_l] + \sqrt{E_p} p_k[m-\tau_l]} \hat{y}_{k,l}[m] \\ &= \frac{\sqrt{E_d} d_k[m-\tau_l] + \sqrt{E_p} p_k[m-\tau_l]}{\sqrt{E_d}\tilde{d}_k[m-\tau_l] + \sqrt{E_p} p_k[m-\tau_l]} h_{k,l}[m] \\ &\quad + \frac{I[m]}{\sqrt{E_d}\tilde{d}_k[m-\tau_l] + \sqrt{E_p} p_k[m-\tau_l]} \end{aligned} \tag{4}$$

where $\hat{h}_{k,l,m}^{LS}[m]$ is the estimated channel coefficient of lth path for kth user at sample instant m.

Since the chip rate is very high, it is reasonable to assume that the channel does not change over a large number of chips. Hence we apply a moving-average-window (MAW) to reduce the estimation error, given by

$$\hat{h}_{k,l}^{LS}[m] = \frac{1}{N} \sum_{i=m-N/2}^{m-1+N/2} \hat{h}_{k,l,m}^{LS}[m] \tag{5}$$

where N is the length of the MAW.

The channel coherent time is given by [13]

$$T_c \approx \frac{1}{f_m} = \frac{c}{f_c v} \tag{6}$$

where f_m denotes the maximum Doppler frequency shift, f_c is the carrier frequency, c is the speed of light and v is speed

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of the mobile user. It is required that $N \ll \frac{T_c}{T}$, where T is the chip interval.

The LS channel estimator in (5) is biased as

$$E\left(\hat{h}_{k,l}^{LS}[m]\right) = \frac{E_d\sqrt{E(\|\tilde{d}_k\|^2)+E_p}}{E_d E(\|\tilde{d}_k\|^2)+E_p} h_{k,l}[m] \geq h_{k,l}[m] \quad (7)$$

where $E(.)$ denotes the expectation operator. Therefore we normalize the LS estimator by $\frac{E_d\sqrt{E(\|\tilde{d}_k\|^2)+E_p}}{E_d E(\|\tilde{d}_k\|^2)+E_p}$ to generate an unbiased LS estimator. We denote the normalized LS estimator as $\hat{h}_{k,l}^{NLS}$.

B. Maximal Ratio Combining (MRC) Channel Estimator

The signal after MAI/ISI cancellation is given in (3), which can be further separated into pilot and data partial signals, given by

$$\begin{aligned} \hat{y}_{k,l,p}[m] &= \hat{y}_{k,l}[m] - \tilde{h}_{k,l}[m]\sqrt{E_p}\tilde{d}_k[m-\tau_l] \\ &\approx h_{k,l}[m]\sqrt{E_p}p_k[m-\tau_l] + I[m] \quad (8) \\ \hat{y}_{k,l,d}[m] &= \hat{y}_{k,l}[m] - \tilde{h}_{k,l}[m]\sqrt{E_p}p_k[m-\tau_l] \\ &\approx h_{k,l}[m]\sqrt{E_d}d_k[m-\tau_l] + I[m] \quad (9) \end{aligned}$$

Two preliminary channel estimations are performed as

$$\begin{aligned} \hat{h}_{k,l,p}[m] &= \frac{1}{\sqrt{E_p}}p_k^*[m-\tau_l]\hat{y}_{k,l,p}[m] \\ &\approx h_{k,l}[m] + \overbrace{\frac{1}{\sqrt{E_p}}p_k^*[m-\tau_l]I[m]}^{\mathrm{n_{k,l,p}}} \quad (10) \\ \hat{h}_{k,l,d}[m] &= \frac{1}{\sqrt{E_d}}\tilde{d}_k^*[m-\tau_l]\hat{y}_{k,l,d}[m] \\ &\approx \sqrt{E\left(\|\tilde{d}_k[m-\tau_l]\|^2\right)}h_{k,l}[m] \\ &\quad + \overbrace{\frac{1}{\sqrt{E_d}}\tilde{d}_k^*[m-\tau_l]I[m]}^{\mathrm{n_{k,l,d}}} \quad (11) \end{aligned}$$

Although the pilot-aided estimates $\hat{h}_{k,l,p}$ produce coarse channel information, their low power allocation limit the performance. On the other hand, the data-derived estimates $\hat{h}_{k,l,d}$ suffer from bias due to the imperfect feedback information on data, especially in the first couple of decoding iterations. In the following we present an enhanced channel estimator by efficiently combining preliminary statistics in (10) and (11).

We model the combined channel estimator as

$$\begin{aligned} \hat{h}_{k,l,m}^{MRC}[m] &= w_1 h_{k,l,p}[m] + w_2 h_{k,l,d}[m] \\ &= \left(w_1 + w_2\sqrt{E(\|\tilde{d}_k[m-\tau_l]\|^2)}\right)h_{k,l}[m] \\ &\quad + (w_1 n_{k,l,p} + w_2 n_{k,l,d}) \quad (12) \end{aligned}$$

where the optimal weights, w_1 and w_2, can be found by minimizing the mean square error (MSE) under the unbiased constraint, given by

$$\begin{aligned} w_{opt} &= \arg\min_{w_1,w_2}\left(w_1^2\sigma_p^2 + w_2^2\sigma_d^2\right) \\ &\quad +\eta(w_1 + w_2\sqrt{E(\|\tilde{d}_k[m-\tau_l]\|^2)} - 1) \quad (13) \end{aligned}$$

where σ_p^2 and σ_d^2 are the variance of $n_{k,l,p}$ and $n_{k,l,d}$ respectively, and η is the Lagrange multiplier. Solving (13) we obtain the optimal weights as

$$w_1 = \frac{1}{\frac{E_d}{E_p}+1} \quad (14)$$

$$w_2 = \frac{\frac{E_d}{E_p}}{\sqrt{E(\|\tilde{d}_k[m-\tau_l]\|^2)}(\frac{E_d}{E_p}+1)} \quad (15)$$

Similar to LS channel estimator, we apply a MAW around the sample instant of interest to obtain the final MRC estimator denoted as $\hat{h}_{k,l}^{MRC}$.

C. MSE Analysis

The performance of channel estimation is limited by the well known Cramer-Rao lower bound (CRLB) [14]. Given the signal model in (3), the corresponding CRLB for estimation over a length-N MAW is given by

$$MSE_{CRLB} = \frac{1}{N}\frac{N_0}{E_d+E_p} \quad (16)$$

However, the CRLB is loose for algorithms based on soft decoded data. In this section we take soft decoded data into account to derive a lower bound which can reflect the reliability of the soft decoding information. To that end, we assume that the soft decoded data can be modelled as

$$\tilde{d} = \mu d + e \quad (17)$$

where $\mu = E(\|\tilde{d}\|)$, and e is a zero-mean Gaussian random variable with variance $\sigma_e^2 = 1 - E(\|\tilde{d}\|)^2$. This model is accurate when the soft decoded data are relatively reliable, i.e. σ_e^2 is small. Then the signal model of the channel estimator can be written as

$$\begin{aligned} \hat{y}_{k,l}[m] &= \left(\frac{\sqrt{E_d}\tilde{d}_k[m-\tau_l]}{\mu} + \sqrt{E_p}p_k[m-\tau_l]\right)h_{k,l}[m] \\ &\quad + \frac{\sqrt{E_d}e}{\mu}h_{k,l}[m] + I[m] \quad (18) \end{aligned}$$

We assume the channel does not change within the MAW. The new lower bound from N observations is given by

$$MSE_{RBLB} = \frac{1}{N}\frac{\frac{E_d\sigma_e^2}{\mu^2}E\left(\|h_{k,l}\|^2\right)+\sigma_I^2}{E_d+E_p} \quad (19)$$

where $\sigma_I^2 = KE_d\left[E(\|\tilde{d}\|)-1\right]^2 + N_0$ is the variance of I and $E\left(\|h_{k,l}\|^2\right)$ represents the average power in lth path for user k. We call this lower bound the reliability-based lower bound (RBLB). It can be shown that $MSE_{RBLB} \geq MSE_{CRLB}$, i.e. the RBLB is tighter than the CRLB. The two lower bounds are the same when the soft decoded data is fully reliable.

We also compare the MSE between different channel estimators to assess their performance. Clearly the biased LS

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estimator, $\hat{h}_{k,l}^{LS}$, has larger MSE than the unbiased LS estimator, $\hat{h}_{k,l}^{NLS}$. It can be shown that the MSEs of $\hat{h}_{k,l}^{NLS}$ and $\hat{h}_{k,l}^{MRC}$ are given by

$$MSE^{NLS} = \frac{1}{N}\frac{1+\frac{E_d}{E_p}E(\parallel \tilde{d} \parallel^2)}{\left(1+\frac{E_d}{E_p}\sqrt{E(\parallel \tilde{d} \parallel^2)}\right)^2}\sigma_p^2 \quad (20)$$

$$MSE^{MRC} = \frac{1}{N}\frac{1}{1+\frac{E_d}{E_p}}\sigma_p^2 \quad (21)$$

To compare the performance between normalized LS estimator and MRC estimator, we calculate the ratio between their MSEs as

$$\beta = \frac{MSE^{NLS}}{MSE^{MRC}} = \frac{(1+\frac{E_d}{E_p})\left(1+\frac{E_d}{E_p}E(\parallel \tilde{d} \parallel^2)\right)}{\left(1+\frac{E_d}{E_p}\sqrt{E(\parallel \tilde{d} \parallel^2)}\right)^2}$$
$$= \frac{(\frac{E_d}{E_p})^2 E(\parallel \tilde{d} \parallel^2)+1+\frac{E_d}{E_p}\left(E(\parallel \tilde{d} \parallel^2)+1\right)}{(\frac{E_d}{E_p})^2 E(\parallel \tilde{d} \parallel^2)+1+\frac{E_d}{E_p}2\sqrt{E(\parallel \tilde{d} \parallel^2)}} \geq 1 \quad (22)$$

The ratio equals 1 when $E(\parallel \tilde{d} \parallel^2) = 1$, i.e. the soft decoded data become fully reliable.

From the MSE analysis, we show that the MRC estimator yields the best performance, while the biased LS estimator performs the worst. All three estimators produce more accurate channel estimations as the iterative decoding proceeds. The unbiased LS estimator will eventually converges to the MRC estimator provided the data decoding is successful.

IV. ESE AND DEC FUNCTIONS

The ESE performs MAI/ISI cancellation described in Section II, and computes the LLRs of the transmitted data. The DECs perform standard APP decoding using the ESE outputs, and also generate extrinsic LLRs. We follow the approach in [2] to compute LLRs for the coherent receiver. Unlike [2] [12], we do not assume that the channel estimates to be perfect. In fact we include the variance of the channel estimation into the ESE functions.

The received signal is given in (2). We model the true channel coefficient as

$$h = \hat{h} + e_h \quad (23)$$

From the central limit theorem, e_h is a Gaussian random variable with variance σ_h^2, which is calculated from the channel estimator. We re-write the received signal as

$$r[m+\tau_l] = \hat{h}_{k,l}[m+\tau_l]\sqrt{E_d}d_k[m] + \zeta_{k,l}[m] \quad (24)$$

where $\zeta_{k,l}$ includes the Gaussian noise, residual interference and channel estimation error effect in the received signal from lth path when the transmitted signal is d_k. Then the ESE output is given by

$$\lambda^{ESE}(d_k)[m] = \quad (25)$$
$$\sum_{l=0}^{L} 2 \parallel \hat{h}_{k,l} \parallel^2 \sqrt{E_d}\frac{Re\left(\hat{h}_{k,l}^*[m+\tau_l]r[m+\tau_l] - E\left(\hat{h}_{k,l}^*[m+\tau_l]\zeta_{k,l}[m]\right)\right)}{Var\left(Re\left(\hat{h}_{k,l}^*[m+\tau_l]\zeta_{k,l}[m]\right)\right)}$$

where $Re(.)$ and $Var(.)$ indicate the real part and the variance operator respectively. The DECs carry out standard APP decoding using $\lambda^{ESE}(d_k)$. The extrinsic LLR output from DECs, $\lambda^{DEC}(d_k)$ are used to generate the soft decoded data, given by

$$\tilde{d}_k[m] = tanh\left(\frac{\lambda^{DEC}(d_k)[m])}{2}\right) \quad (26)$$

V. NUMERICAL RESULTS

In this section, we simulate an IDMA system with $K = 15$ users and rate-1/10 repetition code only, i.e. a loading factor of 1.5. The chip rate is 600kcps. A fading channel that has three equal power delayed paths is used. The carrier frequency is 5GHz and the speed of the mobile users is chosen to be 60km/h. This overloaded system together with the multipath fading channel place a critical condition for channel estimation.

Fig. 2 shows the MSE performance of the iterative channel estimators. Overall our MRC method gives the best performance. At the start of the iterative process, there is no soft decoded data available to the channel estimator. Therefore the LS method, normalized LS method and the MRC method are equivalent to each other, which leads to the same MSE performance at the first iteration in Fig. 2(a). As the iterations proceed, it is shown that the LS method performs much worse than the normalized LS method and the MRC method at the same number of iterations. The difference between normalized LS and MRC is relatively small. For example, the MSE difference at the 10th iteration between these two estimators is approximately 10^{-3} when E_b/N_0=12dB. We also include the RBLB for the 10th iteration as well as the CRLB in the figure. It can be seen that the RBLB is a tighter lower bound than CRLB, which agrees with previous analysis. We see that the MSE of the MRC method approaches the RBLB with a gap of approximate 2dB.

Similar results are found in Fig. 2(b), where MSEs over iterations are shown at E_b/N_0=10dB. The MSEs of different estimators are close at the first couple of iterations due to the poor reliability of the soft decoded data, while their performance diverges at later iterations. The MSE of MRC method converges to the lower bounds with 10 iterations.

Fig. 3 shows the bit error rate (BER) performance of the coherent receiver. Again, we see that the receiver using MRC channel estimation method has the best performance. The normalized LS method performs nearly as good as the MRC method at large number of iterations, both of which achieve less than 2dB difference from the BER of perfect channel scenario at the 10th iteration.

VI. CONCLUSION

In this paper, we have developed an coherent receiver for IDMA systems with integrated channel estimation for multipath time-varying channels. We studied three different low-complexity iterative channel estimation methods which make use of both pilots and soft decoded data. In particular, the MRC approach minimizes the MSE by assigning optimal

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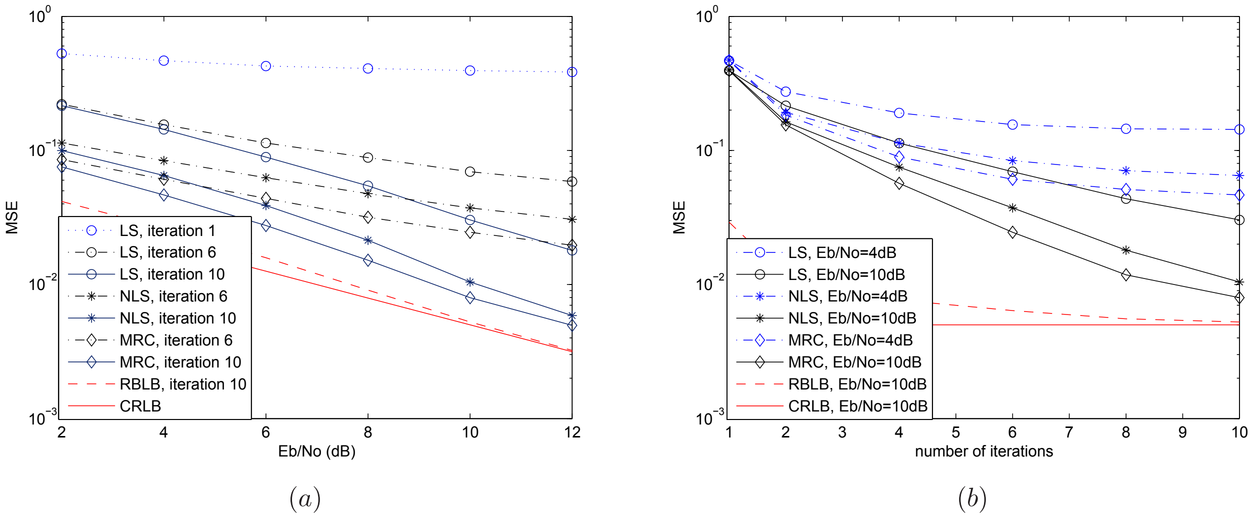

Fig. 2. MSE performance of the channel estimators in a multipath fading channel

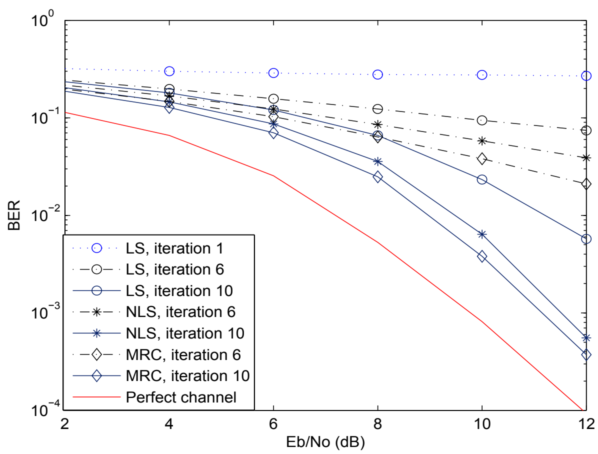

Fig. 3. BER performance in a multipath fading channel

weights to the preliminary channel estimates from the pilot and soft decoded data. It achieves better BER performance compared with LS methods. We also derive a lower bound for the channel estimator, which reflect the reliability of soft decoded data information. We show that the MRC and normalized LS method converge to the bound.

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