An Efficient Algorithm Assisted Minimum Bit Error Rate Multiuser Detector for DS-CDMA Systems in Time-Varying and Frequency-Selective Fading Channels

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Abstract—A minimum bit error rate (MBER) multiuser detector (MUD) is considered for Direct-Sequence Code-Division Multiple-Access (DS-CDMA) communication systems with time-varying and frequency-selective fading channels. The BER cost function of the proposed MBER MUD is highly non-linear and may have several local minimum. It is shown that with some appropriate constraints the BER cost function of the MBER MUD is equivalent to a constrained optimization problem which has a unique global minimum in the feasible region. An efficient Newton method with a barrier parameter is developed for finding the coefficients of the proposed MBER MUD. The BER performance of the MBER MUD is compared to decorrelating (DEC) detector, linear minimum mean-square error (LMMSE) detector, and the maximum likelihood detector for time varying and Rayleigh distributed frequency-selective fading DS-CDMA channels. Monte-Carlo simulations show that the BER of the MBER MUD can be significantly lower than that of the DEC and the LMMSE multiuser detectors.

Keywords-constrained optimization problem; minimum bit-error rate; multiuser detector

I. INTRODUCTION

In DS-CDMA communications system the main operation of the receiver is detection of the information signals of the users. Multiuser detectors suppress the multiple access interference (MAI) in DS-CDMA systems. The conventional matched-filter (MF) receiver is the simplest linear multiuser detector (MUD). The MF receiver is optimal for only a synchronous orthogonal case of the CDMA systems [1]. The decorrelating (DEC) detector and the linear minimum mean-square error (LMMSE) detector are two other more conventional and successful linear multiuser detectors which minimize the multiple access interference (MAI) [2] and the mean-squared error (MSE) [3] respectively. The decorrelating detector employs a linear filter to suppress the MAI completely. Similarly, the LMMSE detector chooses the linear filter to minimize the MSE between the transmitted and the received signals. However, the decorrelating and the LMMSE detectors are not capable of providing the lowest bit error rate (BER) among linear detectors. Hence, it is of important interest to develop a new algorithm for multiuser detector that minimizes BER directly. The minimum bit error rate (MBER) MUD that alter the filter coefficients of the linear detectors in order to minimizes the BER cost function can offer better performance than the DEC and the LMMSE detectors in such scenarios.

Some algorithms were proposed in [4], [5], [6], [7] and [8] for achieving the MBER MUD. In [5], a DS-CDMA system with slow flat fading is considered and an adaptive linear one-shot detector is proposed, which employs stochastic gradient algorithm (SGA) for minimizing the average probability of error. An adaptive algorithm for approximating the MBER linear MUD in the presence of intersymbol interference (ISI) and additive white Gaussian noise (AWGN) is proposed in [6]. In [7], a new linear MUD is proposed for a channel with AWGN. In [8], a constrained MBER MUD that minimizes the BER cost function is proposed for an AWGN channel in DS-CDMA system. Nevertheless, these algorithms do not only have more complexity but also require knowledge of the users’ unique signatures. Besides, some of these proposed algorithms may not guarantee whether the solutions find the global minimum. It should also be noticed that all of these algorithms are developed for the AWGN channels in a DS-CDMA system.

Unlike the other studies in the literature, the concentration is given the MBER multiuser detection problem in time-varying and frequency-selective fading DS-CDMA channels for binary signaling. It should be noted that the BER cost function of the system is highly non-linear and several local minimums may exist. However, the BER cost function can be converted into a
constrained optimization problem with appropriate constraints that always include the global minimum. A Newton method including an adaptive barrier parameter is developed for iterations and the Golden-Section method is employed for the line-search directions. Computer simulation results demonstrate the effectiveness of the proposed algorithm.

This paper is organized as follows. In Section II, the system and the channel models are described. The constrained optimization problem and the MBER MUD are proposed in Section III. In Section IV, numerical examples and computer simulation results via the Monte-Carlo simulation method are given. Conclusions are presented in Section V.

II. PRELIMINARIES

A. System Model

A binary phase shift keying (BPSK) reverse link transmission for synchronous DS-CDMA system with K active users is used for the system model. The baseband equivalent system model is shown in Fig. 1.

Time-varying Rayleigh frequency-selective fading channel with L resolvable paths is selected for the channel model and linear filters are employed for modeling the channels.

The signal propagation by k\textsuperscript{th} user is:

\[ s_k(t) = \sqrt{2P_k} b_k(t)a_k(t)\cos(w_c t) \]  

where \( P_k \) is the signal power, \( b_k(t) \) is the data sequence, \( a_k(t) \) is the unique spreading code of the the k\textsuperscript{th} user, and \( w_c \) is the carrier frequency of the system. The spreading code of the k\textsuperscript{th} user is expressed as follows:

\[ a_k(t) = \sum_{j=-\infty}^{\infty} a_{k,j} p_{T_c}(t - jT_c) \]  

where \( a_{k,j} \in \{1, +1\} \) denotes the unique code sequence of the j\textsuperscript{th} chip of the k\textsuperscript{th} user, and \( p_{T_c}(\cdot) \) and \( T_c \) denote the unit rectangular pulse function and chip period respectively. Data sequence for the k\textsuperscript{th} user is expressed below.

\[ b_k(t) = \sum_{j=-\infty}^{\infty} b_{k,j} p_{T_b}(t - jT_b) \]  

where \( b_{k,j} \in \{-1, +1\} \) is the data sequence for the k\textsuperscript{th} user. \( T_b \) denotes the bit period. Assuming that there are N chips, then it can be expressed as \( N = T_b/T_c \). The total signal which is propagated to channel by the all active users can be expressed as follows:

\[ s(t) = \sum_{k=1}^{K} \sqrt{2P_k} a_k(t)b_k(t)\cos(w_c t) \]  

B. Channel Model

Time-varying Rayleigh frequency selective fading channel with L resolvable path is selected for the channel model. In this channel model, bandwidth of the users’ signal is higher than the channel’s bandwidth. Linear filters are employed for modeling these type channels.

Users’ signal passes through the channel; it will be corrupted by channel noise and frequency selective fading. The complex lowpass impulse response of this channel is expressed as:

\[ h_k(t,\tau) = \sum_{l=1}^{L} a_{k,l} e^{-j\theta_k} g(t,\tau_{k,l}) \ast \delta(t - \tau_{k,l}) \]  

where \( \delta(\cdot) \) denotes the Dirac Delta function, \( L \) is the number of multipath between the base station and the desired user, \( l \) is the path index, and \( \{a_{k,l}\}_{l=1}^{L} \), \( \{\theta_{k,l}\}_{l=1}^{L} \), \( \{\tau_{k,l}\}_{l=1}^{L} \) denote the random path amplitude, random path phase, random path delay respectively. \( g(t,\tau) \) is the impulse response of the time-varying frequency selective fading channel, and the symbol \( \ast \) denotes convolution in time domain.

C. Receiver Model

The signal which is transmitted by all of the active users to the channel reaches to the receiver. Received signal expression can be written as follows.

\[ r(t) = s(t) \ast h(t) \]  

\[ r(t) = \sum_{k=1}^{K} \sqrt{2P_k} a_k(t)b_k(t)\cos(w_c t) \]  

\[ \ast \left( \sum_{l=1}^{L} a_{k,l} e^{-j\theta_k} g(t,\tau_{k,l}) \ast \delta(t - \tau_{k,l}) \right) \]
\[ r(t) = \sum_{k=1}^{K} \sum_{l=1}^{L} \sqrt{2P} a_{k,l} g(t, \tau_{k,l}) b_{k,l}(t - \tau_{k,l}) * a_k(t - \tau_{k,l}) \cos[w_c t + \theta_{k,l}] + n(t) \]

\[ r(t) = \sum_{k=1}^{K} \sum_{l=1}^{L} \sqrt{2P} a_{k,l} a_k(t - \tau_{k,l}) g(t, \tau_{k,l}) b_{k,l}(t - \tau_{k,l}) \cos[w_c(t - \tau_{k,l}) + \theta_{k,l}] + n(t) \]

\( n(t) \) is the AWGN signal with zero mean and variance \( \sigma^2 \). After the matched filter bank in the receiver, output of the received signal is

\[ y = \int_0^T r(t) a_k(t) \, dt \quad k = 1, 2, ..., K \quad (7) \]

### D. System Model

For the discrete-time received signal vector after chip-rate sampling can be expressed in matrix form as,

\[ r = SAh + n \quad (8) \]

where \( r = [r_1, r_2, ..., r_N]^T \) is the received signal, \( S = [s_1 \ s_2 \ ..., \ s_K] \) is a matrix whose columns include the users’ spreading codes, \( H = \text{diag}(h_1, h_2, ..., h_K) \) is the channel matrix, \( h_k = [\alpha_{k,1}, \alpha_{k,2}, ..., \alpha_{k,L}]^T \) is the channel coefficient vector, \( A = \text{diag}([\sqrt{2P_1}, \sqrt{2P_2}, ..., \sqrt{2P_K}]) \) is the diagonal amplitude matrix, \( b = [b_1, b_2, ..., b_K]^T \) is the users’ data vector, and \( n = [n_1, n_2, ..., n_K]^T \) is the Gaussian noise vector with zero mean and variance \( \sigma^2 \) and it is independent of the signal sources. The amplitude matrix \( A \) is time-invariant and the Doppler affected \( \theta_{k,l} \) of \( h_k \) is time-variant. The cross correlation matrix of the users’ spreading code can be written as;

\[ R_{kj} = \rho_{kj} = \int_0^T a_k(t) a_j(t) \, dt = S^T S \quad (9) \]

It is assumed that, \( R \) is positive definite matrix. The linear multiuser detector can be regarded as an FIR filter and its output is given below:

\[ y = w^T r \quad (10) \]

where \( w = [w_1, w_2, ..., w_N]^T \) denotes the coefficient vector for the proposed linear MBER MUD of length \( N \).

### III. MBER MULTIUSER DETECTION

The BER cost function for the user 1 can be found in [8] as:

\[ P(w) = \frac{1}{2^{K-1}} \sum_{k=1}^{K} Q \left( \frac{A_k S_k w^T b_k}{\sigma \|w\|} \right) \quad 1 \leq k \leq 2^{K-1} \quad (11) \]

where \( Q(x) = (2\pi)^{-1/2} \int_x^\infty e^{-u^2/2} \, du \) is the Gaussian cumulative distribution function. Any \( w^* \) which minimizes the BER cost function \( P(w) \) in Eq. 11 can be referred as the MBER MUD and the purpose of this study is finding the \( w^* \). However, there is no closed-form expression for \( w^* \) well, then the next equation can be used to convert Eq. 11 into a constrained optimization problem:

\[ w_{\text{MBER}} = \arg\min P(w) \quad (12) \]

\[ \min \quad P(w) = \frac{1}{2^{K-1}} \sum_{k=1}^{K} Q \left( \frac{A_k S_k w^T b_k}{\sigma \|w\|} \right) \]

\[ \text{s.t.} \quad \frac{A_k S_k w^T b_k}{\sigma \|w\|} \geq 0 \quad 1 \leq k \leq 2^{K-1} \]

Since the BER cost function is independent of the coefficient vector’s length, the BER cost function can be analyzed on the set \( \|w\| = 1 \).

\[ \min \quad P(w) = \frac{1}{2^{K-1}} \sum_{k=1}^{K} Q \left( \frac{w^T r_k}{\sigma} \right) \quad (13) \]

\[ \text{s.t.} \quad \|w\| = 1, \frac{w^T r_k}{\sigma} \geq 0 \quad 1 \leq k \leq 2^{K-1} \]

Any local minimum of the BER cost function in Eq. 13 is the global minimum. Furthermore, with the constraint \( \|w\| = 1 \), the global minimum is unique [7]. Because of the feasible region which is characterized by constraints in Eq. 13 is not convex, the BER cost function in Eq. 13 do not match for convex programming problem. However, it can be easily converted to convex programming problem with the constraint \( \|w\| \leq 1 \). Since the solution of the constrained optimization problem in Eq. 13 corresponds the solution of the problem with the constraint \( \|w\| \leq 1 \).

\[ \min \quad P(w) = \frac{1}{2^{K-1}} \sum_{k=1}^{K} Q \left( \frac{w^T r_k}{\sigma} \right) \quad (14) \]

\[ \text{s.t.} \quad \|w\| \leq 1, \frac{w^T r_k}{\sigma} \geq 0 \quad 1 \leq k \leq 2^{K-1} \]
The difference between Eq. 13 and Eq. 14 is that the latter one is the convex programming problem where several algorithms are available for.

The proposed minimization algorithm includes three sections such as: constructing a barrier parameter by using adaptive barrier method, finding the convergence direction with Golden-Section method, and choosing suitable initial vector within the feasible region.

In Eq. 6, the non-linear constraint can be dropped and converted the equation into the form as given below:

\[ \min F_{\mu}(w) = P(w) - \mu \log(1 - w^T w) \]  
\[ \quad \text{s.t.} \quad \frac{w^T r_k}{\sigma} \geq 0 \quad ; \quad 1 \leq k \leq 2^{K-1} \]

where \( \mu \) is a barrier parameter and \( \mu > 0 \). If the initial coefficient vector \( w_0 \) is chosen in the feasible region, it satisfies the constraints in Eq. 14. The Gradient and Hessian of the \( F_{\mu}(w) \) are given by in [7]:

\[ \nabla F_{\mu}(w) = -\sum_{k=1}^{2^{K-1}} \frac{1}{2} e^{-\Lambda_k/2} \frac{r_k}{||w||^2} + \frac{2\mu w}{1-||w||^2} \]

\[ \nabla^2 F_{\mu}(w) = \sum_{k=1}^{2^{K-1}} \frac{1}{2} e^{-\Lambda_k/2} r_k r_k^T + \frac{2\mu}{1-||w||^2} I \]

(16) \]

(17) \]

where \( \Lambda_k = w^T r_k \) and \( I \) is the unit matrix. Then, proposed iteration procedure can be explained as:

\[ w_{k+1} = w_k + \zeta_k \Omega_k \]

(18)

where \( \Omega_k \) is the search direction and it can be written as:

\[ \Omega_k = -\frac{1}{||w||^2} \nabla F_{\mu}(w) \]

(19)

\[ \zeta_k \]

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The performance of the proposed MBER MUD with the LMMSE and the decorrelating detectors is compared. The parameter sets are:

$A_1 = 1, \quad A_2 = 0.56, \quad A_3 = 0.28$

$s_1 = [1 \ 0 \ 0]^T,$

$s_2 = [0.28 \ 0.56 \ 0]^T,$

$s_3 = [-0.56 \ 0.28 \ 0.62]^T$

$\sigma = 1, \quad w_0 = [0.5 \ 0.3 \ 0.1]^T$

$b_1 = [1,1,1], \quad b_2 = [-1,1,-1], \quad b_3 = [-1,-1,1]$

The coefficient vectors of the DEC and the LMMSE detectors are calculated exactly, whereas the MBER MUD coefficient vector was obtained via the proposed algorithm. In the Monte-Carlo simulations, the MBER MUD was taken as the global minimum for Eq. 15 of 68 runs of the proposed minimization algorithm. For these parameters, the optimum linear MBER MUD is given by:

$$w^* = \begin{bmatrix} -0.1036 \\ 1.0088 \\ -0.3545 \end{bmatrix}$$

The coefficient vector equations for the decorrelating and the LMMSE detectors are given by [8]:

$$w_{DEC} = S(S^T S)^{-1} H^{-1} A^{-1}$$  \hspace{1cm} (22)

$$w_{LMMSE} = S(S^T S + \sigma^2 H^{-2} A^{-2})^{-1} H^{-1} A^{-1}$$ \hspace{1cm} (23)

If coefficient vectors for the LMMSE and the decorrelating detectors are computed, the below vectors are obtained:

$$w_{lmmse} = \begin{bmatrix} -0.2799 \\ 2.3940 \\ 0.1561 \end{bmatrix}, \quad w_{dec} = \begin{bmatrix} -0.2961 \\ 2.0806 \\ 0.2045 \end{bmatrix}$$

The BER curves of the multiuser detectors are illustrated in Fig. 3 and the desired user is user 1. The BER performances of the detectors generally decrease with respect to mean SNR. The study finds that the proposed MBER MUD has more than 2 dB gain over the LMMSE detector at BER=10^{-3}. The MBER MUD outperforms the decorrelating detector by about 3.5 dB for BER=10^{-3}. Observe that the LMMSE and the DEC curves are nearly indistinguishable for low values of SNR. On the other hand, the MBER MUD’s curve is drastically different from the other curves for especially high SNR region. The BER values of the multiuser detectors for the values of SNR are given in Table 1.
Note that, in the high SNR region, the performance of the MBER MUD detector was nearly equal to that of the maximum-likelihood (ML) detector [1].

For comparison purposes, the BER performances of the multiuser detectors for AWGN, frequency-selective, and time-varying frequency-selective fading channels were also simulated. As can be seen in Fig. 3, MBER MUD outperforms all other detectors in the AWGN channel. Observe from Fig. 4 that the performance of the MBER MUD in the AWGN channel is higher than 4 dB from the performance of the DEC detector. With time-varying frequency-selective fading channel, the gain of the MBER MUD drops to slightly more than 2 dB.

Table I. BER versus SNR

<table>
<thead>
<tr>
<th>SNR in dB</th>
<th>BER for Multiuser Detectors</th>
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<tbody>
<tr>
<td></td>
<td>DEC</td>
</tr>
<tr>
<td>2</td>
<td>0.1381</td>
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<tr>
<td>4</td>
<td>0.0978</td>
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<tr>
<td>15</td>
<td>0.0024</td>
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<tr>
<td>16</td>
<td>0.0016</td>
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</tbody>
</table>

B. Example 2

In this example, the performance of the multiuser detectors are compared for different number of active users in the system. The N=21 chips signature codes of the users are assigned randomly and the perfect power control for all users is assumed (Near-Far Ratio = 0 dB).

The users’ signal amplitudes are employed as a uniform random numbers in [0,1]. Unlike the first example, the multipath scenario is considered with L=3 paths. The number of active users is limited by the length of the users’ code sequences. Fig. 5 depicts the BER versus SNR curves for different number of users in the system.

As can be seen in the Fig. 5, the BER performance of the MBER MUD degrades dramatically when the number of active users is high. That’s why; the MBER MUD becomes interference limited as the number of active users increases. The number of chips for the signature codes can be increased for improving the BER performance. Furthermore, sufficiently large values of SNR of the desired user provide the better BER performance.
C. Example 3

In the third example, similar with the previous one, the BER performances of the multiuser detectors are considered with the multipath channel parameter is $L=2$ and $N=31$ chips Gold-Codes for the users’ signature sequences. However, the Monte-Carlo simulations are performed to find the required SNR gains of the MBER MUD at $BER=10^{-2}$. The required SNR curves are illustrated in Figure 6.

The performance of the LMMSE detector is similar to that of the DEC detector, whereas the MBER MUD offers a performance gain as much as 4.5 dB over the DEC detector. After a point, the required SNR asymptotically converges to a value. This value changes according to the number of users’ chips.

D. Example 4

As the last example, the performance of the proposed MBER MUD is compared for different Near-Far Ratio values, defined as the power ratio between the desired user and the interferers $(20 \log(P_d/P_i))$. It is assumed a five-user system with $N=31$ chips Gold-Code and the first user is desired user which has unit energy and the SNR is 14 dB. Unlike the first user, it is chosen from 1 dB to 16 dB for the other users as a Near-Far Ratio values. In this scenario with Near-Far Ratio of 12 dB, the proposed MBER MUD is useless as its BER cannot descend below 0.02. The Near-Far ratio performances of the detectors are illustrated in Fig. 7.

V. CONCLUSIONS

The MBER MUD for time-varying and Rayleigh frequency-selective channels on DS-CDMA system is studied.

![Figure 6. SNR curves for different number of active users for providing the average BER value of $10^{-2}$.](image)

![Figure 7. BER curves for different Near-Far Ratio values.](image)

It is also discussed the constrained optimization problem for minimization algorithm in detail. The most important factor that distinguishes this work from others in the literature is the usage of time-varying channel model instead of using the AWGN or using only fading channel models as in the previous studies. The BER cost function of multiuser detection for time-varying Rayleigh frequency-selective fading DS-CDMA channels is studied and converted into an equivalent constrained optimization problem. Then MBER MUD algorithm which approaches the minimum BER performance is proposed. The proposed detector algorithm minimizes the BER cost function subject to the constraint that is a convex set of the feasible region.

The analysis and simulations results confirm that the proposed MBER MUD minimizes the BER cost function and can achieve lower BER than the decorrelating and the LMMSE detectors in medium or high SNR cases. Furthermore, the MBER MUD has a lower complexity than the ML multiuser detector but achieves approximately similar/parallel BER performance. Increasing the number of chips for the signature codes improves the BER performance of the MBER MUD substantially.

REFERENCES


