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Iterative Total Least-Squares Algorithm for Joint Detection via the Conjugate Gradient Method

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Abstract

Joint detection (JD) known as a multi-user detection technique can combat both the inter-symbol interference (ISI) and multiple access interference (MAI). However, it depends on the accuracy of channel estimation. In multipath fading channels, the error of channel estimation is inevitable, and it will propagate to system matrix. In this paper, we analyze the effect of channel estimation error on joint detection. After analyzing perturbation of least squares problems, we present a new joint detection method based on total least-squares (TLS) criteria. Here, we propose an iterative total least-squares algorithm that minimizes the error of system matrix and noise. The proposed method is given by using a conjugate gradient method which is particular suitable for very large matrices. Simulation results confirm our theoretical analysis. Additionally, it is shown the performance of proposed equalize scheme is better than zero forcing block linear equalizer (ZF-BLE).

***Keywords**: Joint detection, channel estimation error, total least squares (TLS), conjugate gradient, TD-SCDMA*

1. Introduction

The third generation cellular communication systems are based on code division multiple access (CDMA) technology, which has characteristics supporting flexible and high rate services. In real implementation, CDMA systems suffer from Multiple Access Interference (MAI), which affects all users equally. With the increase of signal power, MAI becomes a major problem to the broadband CDMA communication system. The conventional RAKE receiver only consider single user's signal information and do not take into account the interference from all other users in the system. The orthogonality of the spreading codes is destroyed after transmission over time dispersive multipath channels. Thus, there is an irreducible bit error rate (BER) floor if the RAKE receiver is used. Joint measuring technology is critical to 3G system and is designed to process all users in parallel by including the interference information from the other users.

In this paper, we consider the time division synchronous code division multiple access (TD-SCDMA) system, which is based on the combination of TDMA, CDMA, SDMA and FDMA technologies. TD-SCDMA systems support flexible and high rate services, being developed initially for People's Republic of China. It includes sophisticated techniques such as smart antennas and joint detection to improve system performance [1]. In [2], space-time joint detection technology is employed by combining joint detection with smart antenna. Joint Detection scheme is prohibited since its complexity grows exponentially as the number of user increases. Because most of the operations are matrix and vector, the sizes of the matrices and vectors increase as the number of the users increase. In order to degrade the complexity, there are two types of sub-optimization joint detector: linear and non-linear. The non-linear approach is much more efficient than the linear one, but it is much more difficult in terms of the implementation complexity. In

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TD-SCDMA system, the complexity can be reduced by limiting the number of users in a given time slot.

Currently, linear joint detection techniques have been advocated in TD-SCDMA system [3-4]. Based on different criteria, there are three kinds of linear joint measured methods: Whitening Matched Filtering (WMF) calculation, Zero Forcing Block Linear Equalizer (ZF-BLE) calculation and Minimum Mean Square Error-Block Linear Equalizer (MMSE-BLE) [5] calculation, respectively. WMF is based on the principle of maximum signal to noise ratio, but it fails to solve fully the problems of ISI and MAI interference. Due to the simple and easy operation, WMF is the foundation of ZF-BLE and MMSE-BLE. ZF-BLE and MMSE-BLE are used to solve problems resulted from ISI and MAI, and their performance is compared in [6]. However, requiring the estimations of noise variance and a large amount of computation, MMSE-BLE method is more efficient than the ZF-BLE method. By using smart antenna, space-time joint detection [7, 8] is employed in the uplink receiver. In the circumstance of using smart aerial, the performance difference between ZF-BLE and MMSE-BLE gets smaller, especially in case of more user numbers and the wireless channel environment gets worse. Taken into the comprehensive consideration, ZF-BLE has been the implementation method of joint measuring technology.

However, the performance of joint detection depends on the fast and precise estimation of wireless channel impulse responses (CIRs). Traditional channel estimation methods of CDMA system [9] cannot meet the requirements of rapidity and real-time, because all these methods usually perform massive matrices inverse operations. In TD-SCDMA systems, a midamble is transmitted during each time slot for channel estimation. B. Steiner [10-11] presented a low-cost channel estimation algorithm based on the Least Square (LS) optimization method. This approach assumes that the channel is essentially static over the entire slot, and it simplifies the complicated linear convolution operation, which increases the operation speed of channel estimation algorithm. Based on comparing the power of channel's taps and the noise power according to a defined threshold rule, methods have been proposed to improve the B. Steiner channel algorithm in [12-13]. Because the above algorithms simply treat inter-cell interference as noise, the results of channel estimation will be greatly decreased due to the noise. Therefore, some multi-cell channel estimation (MCE) algorithms such as minimum mean-square-error (MMSE) are presented in [14]. To reduce the computational complexity with better performance, in [15] implements the transposition of square matrix instead of inverse operation by PN-sequence. Song XQ [16] proposes an iterative parallel interference cancellation channel estimation algorithm. By adopting Singular Value Decomposition (SVD), Ali K [17] presents a novel channel estimation method with low complexity.

Channel estimation is a process of estimating parameters of some presumed channel models by receiving data. The channel estimation is got through short training sequences in TD-SCDMA systems, which will cause error of the channel estimation. The effective channel estimation is the estimation algorithm resulting to minimize estimation error. For time-varying environments, reliable channel estimate can't be provided by channels estimation techniques. So, the error of channel matrix can hardly be avoided. Most of joint channel estimation leads to an irreducible BER floor. According to the error propagation law, the system matrix is also incorrect, which introduces significant errors into the detected data of multiple users.

However, most of previous works did not further present the impact of the accuracy of channel estimation on the JD operation. In this paper, we present a novel equalizer based on the total least squares (TLS) criterion [18] for recover data. Zero forcing block linear equalizer is based on least squares (LS) criterion. The greatest advantage of ZF-BLE is its simple structure, lowly complexity. However, the least squares solution is vulnerable to the interference or error, so the accuracy of this algorithm is limited. We will give an analysis for perturbation of least squares. The restoration of an input signal from a measured system output is usually classified as an ill-posed problem [19]. Because the presence of measurement errors may lead to noise amplification that becomes significant in signal restoration, there exists the error of system matrix. The total least-squares (TLS) technique is well used to solve this kind of problem [20, 21]. In most reported studies the TLS problem is solved by SVD [22]. In general, the SVD calculation needs $O(n^3)$ multiplications. Therefore the SVD-based method is not suitable for large-scale systems. Total least squares has not however been applied to joint detection, perhaps due to lack of efficient algorithms for solving the required eigenvalue problem. Toward this goal, the conjugate gradient CG method can be applied here. The conjugate gradient CG method usually requires $O(n^2)$ multiplications per iteration, but the conjugate gradient CG method converges very fast and is particularly used to handle large matrices [23-24]. Therefore, the TLS solution is obtained by minimizing a Rayleigh-quotient function with use of the conjugate gradient (CG) method, which is suitable for large-dimension data.

This paper is organized as follows. In Section 2 we briefly go over the TD-SCDMA system model and a classic channel estimated algorithm. In Section3, we provide a review of ZF-BLE algorithm, and analyze the perturbation of ZF-BLE and impact of channel estimation error in theory. Joint detection based on TLS criterion is introduced, and the conjugate gradient (CG) algorithm is also present in Section4. Simulations are carried out to evaluate the performance of the proposed scheme in Section5. The conclusion and future work are given in Section6.

2. System Model

In this section, the TD-SCDMA system and channel estimation are introduced.

2.1. TD-SCDMA Frame Hierarchy

The physical constructions of TD-SCDMA system are defined in terms of frequency, time, and code. The TD-SCDMA system provides a support for both circuit-switched data, such as voice, multimedia, and packet-switched data from the internet. For $(1/Tc)$ =1.28 Mcps option of TD-SCDMA system, where Tc is the chip period, each frame interval is 10 ms and it contains two 5 ms subframes and 6400 chips. In this low chip rate mode, each subframe consists of seven regular time slots of 864 chips (675μs duration) which can be flexibly assigned to either multiple users or single user that might require multiple time slots, and three special time slots [11-12]. Three special time slots are respectively DwPTS (downlink pilot time slot) of 96 chips (75 μs), GP (guard period) of 96 chips (75 μs) and UpPTS (uplink pilot time slot) of 160 chips (125 μs), as shown in Figure 1. Time slot is the lasting time of burst. The first time slot TS0 is assigned only for downlink, while time slot TS1 is always allocated for uplink. Fig .1 shows that each regular time slot is composed of two data blocks of 352chips length respectively, a midamble code of 144chips length and a GP with 16chips length. The midamble between the two data bearing blocks is designed to estimate and measure channels. All the digit numbers have the spectrum spread by channel code and interference code, that is to say every data signal has been transmitted into some codes which widen the signal bandwidth.

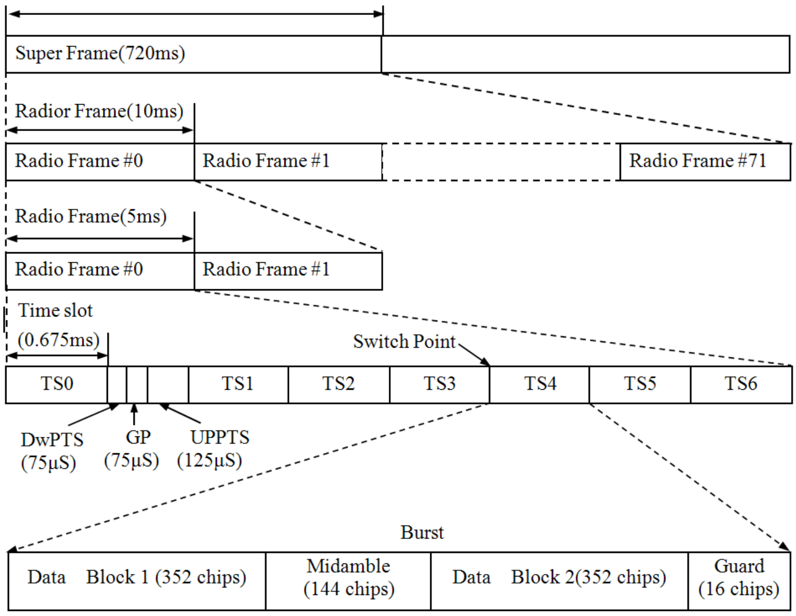


Figure 1. Frame and Burst Structure in TD-SCDMA System

2.2. Signal Model

In order to develop a system model when data are transmitted, it is convenient to take a block transmission system [25], since the TD-SCDMA system is divided in time. We consider a TD-SCDMA downlink with processing gain Q and K active users. The data symbols designed for all K active users are synchronously and simultaneously transmitted from the base station to the mobile units over the same downlink channel. Figure.2 shows a general model of a TD-SCDMA System.

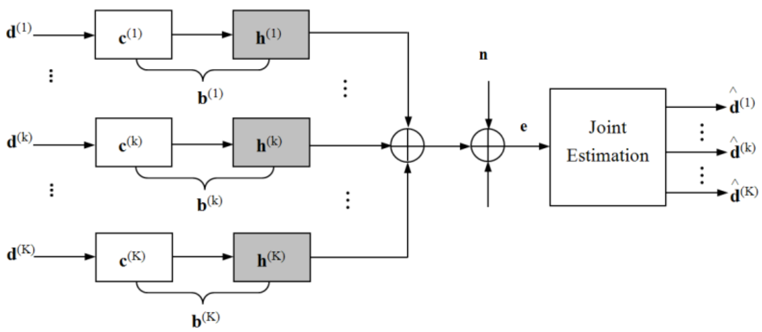


Figure 2. Discrete Base Band Model of a Block Transmission TD-SCDMA System

Within each time slot, N data symbols are transmitted for each of the K users. The data symbols of user k may be written as:

$$\mathbf{d}^k = \begin{bmatrix} d_1^k & d_2^k & \cdots & d_N^k \end{bmatrix}^T \qquad k = 1, 2, \cdots, K \tag{1}$$

where superscript T denotes matrix or vector transposition. It is supposed that each data symbol has normalized energy of units. Each data symbol $d_n^k \quad (n = 1, 2, \cdots, N)$ is spread by the user specific Q-dimensional orthogonal variable spreading factor (OVSF) code

$$\mathbf{c}^k = \begin{bmatrix} c_1^k & c_2^k & \cdots & c_Q^k \end{bmatrix}^T \qquad k = 1, 2, \cdots, K \tag{2}$$

The channel impulse response (CIR) of the kth user can be characterized by

$$\mathbf{h}^k = [h_1^k, h_2^k, \cdots, h_W^k]^T \qquad k = 1, 2, \cdots, K \tag{3}$$

Where W is the length of CIR. It is assumed that the CIR is time-invariant within each time slot. ISI and MAI will arise when W greater than one and orthogonality between OVSF codes had been distortion under channel.

Define the combined channel impulse vector of the kth user as the convolution of the corresponding CIR with the corresponding spreading code:

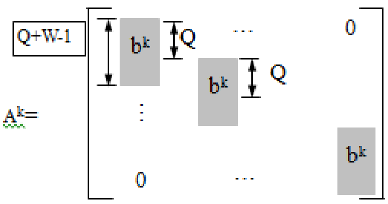
$$\mathbf{b}^{(k)} = [b_1^k, b_2^k, \cdots, b_{Q+W-1}^k]^T = \mathbf{c}^k * \mathbf{h}^k \qquad k = 1, 2, \cdots, K \tag{4}$$

where $*$ is the convolution operation.

The received sequence is received at chip rate. It is the sum of K users, and each has a length of $N \bullet Q + W - 1$ and arrives synchronously. So the received signal $\mathbf{r}$ can be written as:

$$\mathbf{r} = \sum_{k=1}^{K} \mathbf{d}^k \bullet \mathbf{c}^k * \mathbf{h}^k + \mathbf{n} = \sum_{k=1}^{K} \mathbf{A}^k \bullet \mathbf{d}^k + \mathbf{n} = [\mathbf{A}^1 \quad \mathbf{A}^2 \cdots \mathbf{A}^K] \begin{bmatrix} \mathbf{d}^1 \\ \mathbf{d}^2 \\ \vdots \\ \mathbf{d}^K \end{bmatrix} + \mathbf{n} = \mathbf{A}\mathbf{d} + \mathbf{n} \tag{5}$$

Where $\mathbf{A}^k$ is a $(N \bullet Q + W - 1) \times N$ block Toeplitz matrix defined in (6).



(6)

System matrix $\mathbf{A}$ is a $(N \bullet Q + W - 1) \times (KN)$ matrix, which collects the channel matrices into single one. $\mathbf{n}$ is an $KN \times 1$ additive white Gaussian noise (AWGN) vector, with variance $R_{\mathbf{n}} = \sigma^2 \bullet \mathbf{I}$.

2.3. Channel Estimation

In TD-SCDMA system, there are 128 basic midambles which are divided into 32 groups. In each cell, the base station chooses one out of the four midamble codes in a given group and each active user in the cell is assigned with a different cyclically shifted version of this basic midamble [26].

The midamble sequence of user k can be represented as:

$$\mathbf{m}^{(k)} = (m_1^k, m_2^k, \cdots, m_{L_m}^k)^T \qquad k = 1, 2, \cdots, K \tag{7}$$

Themidamblecode will be sent out along with data information to the receiving terminal via wireless channels. The amplitude and phase distortion happened during the transmitting process, so that the received the midamble code is:

$$\mathbf{e}^{(k)} = \mathbf{m}^{(k)} * \mathbf{h}^{(k)} + \mathbf{n}^{(k)} \tag{8}$$

Where $\mathbf{n}^{(k)}$ is additive noise. The convolution operation expressed by (8) can be represented by matrix and vector:

$$e^{(k)} = \begin{bmatrix} m_1^k & 0 & \cdots & 0 \\ m_2^k & m_1^k & \cdots & \cdots \\ \vdots & \vdots & \vdots & 0 \\ m_W^k & m_{W-1}^k & \cdots & m_1^k \\ \vdots & \vdots & \vdots & \vdots \\ m_{L_m}^k & m_{L_m-1}^k & \cdots & m_{L_m-W}^k \\ 0 & m_{L_m}^k & \cdots & m_{L_m-W+1}^k \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & m_{L_m}^k \end{bmatrix} \bullet \begin{bmatrix} h_1^k \\ h_2^k \\ \vdots \\ h_{\mathrm{W}}^k \end{bmatrix} + \begin{bmatrix} n_1^k \\ n_2^k \\ \vdots \\ n_{\mathrm{W}}^k \end{bmatrix} \tag{9}$$

After the W is given, midamble sequence is located between two data fields. The interplay causes the interference between midamble sequence and two data fields. The former W-1 chips midamble codes of receiver are affected by the first data field. The last W-1 chips midamble codes affect the second data field. So the only code decided by midamble sequence is $W \sim W + P$-1. Equation (9) is reset to be:

$$\mathbf{e}^{(k)} = \begin{bmatrix} m_W^{(k)} & m_{W-1}^{(k)} & \cdots & m_1^{(k)} \\ m_{W+1}^{(k)} & m_W^{(k)} & \cdots & m_2^{(k)} \\ \cdots & \cdots & \ddots & \vdots \\ m_{L_m-1}^{(k)} & m_{L_m-2}^{(k)} & \cdots & m_{L_m-W}^{(k)} \end{bmatrix} \bullet \begin{bmatrix} h_1^k \\ h_2^k \\ \vdots \\ h_{\mathrm{W}}^k \end{bmatrix} + \begin{bmatrix} n_1^k \\ n_2^k \\ \vdots \\ n_{\mathrm{W}}^k \end{bmatrix} = \mathbf{G}^{(k)}\mathbf{h}^{(k)} + \mathbf{n}^{(k)} \tag{10}$$

In TD-SCDMA system, midamble sequences of all K users are transmitted simultaneously. Received signals are commonly determined by midamle sequences of all K users and additive noises, as the following equation:

$$\mathbf{e} = \sum_{k=1}^{K} \mathbf{e}^{(k)} = \sum_{k=1}^{K} \left(\mathbf{G}^{(k)}\mathbf{h}^{(k)} + \mathbf{n}^{(k)} \right) = \left[\mathbf{G}^{(1)} \quad \mathbf{G}^{(2)} \quad \cdots \quad \mathbf{G}^{(K)} \right] \begin{bmatrix} \mathbf{h}^{(1)} \\ \mathbf{h}^{(2)} \\ \vdots \\ \mathbf{h}^{(K)} \end{bmatrix} + \mathbf{n} = \mathbf{G}\mathbf{h} + \mathbf{n} \tag{11}$$

Where $\mathbf{G}$ is P order square cyclic matrix that collects $\mathbf{G}^{(k)}$ for all the K users in the same serving cell. At the same time, $\mathbf{h}$ is the $P \times 1$ channel impulse vector for the K users.

The CIR of vector $\mathbf{h}$ can be obtained from (11):

$$\hat{\mathbf{h}} = \mathbf{G}^{-1}\mathbf{e} = \mathbf{h} + \mathbf{G}^{-1}\mathbf{n} \tag{12}$$

The key to $\mathbf{h}$ solve is to find the converse of $\mathbf{G}$ inverse a circular Toeplitz matrix which contains the converse of nonsingular circular matrix. Therefore it only needs to solve the first column and the first row of the circular converse matrix. By using the property of a cyclic matrix, Discrete Fourier Transform (DFT) and Inverse Discrete Fourier Transform (IDFT) can be employed to simplify the calculation greatly [10-11], and therefore the channel of K users can be estimated as:

$$\hat{\mathbf{h}} = IFFT\left(\frac{FFT(\mathbf{e})}{FFT(\mathbf{m}_{basic})} \right) \tag{13}$$

Since different columns of matrix $\mathbf{G}$ generated by the same basic midamble in the serving cell are quasi-orthogonal vectors, the B. Steiner algorithm, applied as a low-computational method, can achieve satisfying performance with little amplification of noise power.

3. Joint Detection Algorithms and Analyze of Error

3.1. Zero Forcing Block Linear Equalizer

Various data detection algorithms associated with determining the data vector $\mathbf{d}$ in (5) have been considered in [3-5]. ZF-BLE algorithm is the optimal weighted least squares estimation based on Gauss-Markov theorem. The solution of ZF-BLE algorithm is obtained by the following equation:

$$\mathbf{q} = \arg\min \left\| \mathbf{r} - \mathbf{A}\hat{\mathbf{d}} \right\|^2 \tag{14}$$

It can obtain a continuous unbiased estimate.

The derivation of ZF-BLE algorithm is given as the following. Assuming noises are uncorrelated, then $R_{\mathbf{n}} = \sigma^2 \mathbf{I}$. The Lagrangian equation of problem Equation (14) is present by:

$$\frac{\partial \mathbf{q}}{\partial(\hat{\mathbf{d}})} = \mathbf{0} \tag{15}$$

According to the derivation rule of the matrix function:

$$\begin{aligned} \frac{\partial \mathbf{q}}{\partial(\hat{\mathbf{d}})} &= \frac{\partial[(\mathbf{r} - \mathbf{A}\hat{\mathbf{d}})^H (\mathbf{r} - \mathbf{A}\hat{\mathbf{d}})]}{\partial(\hat{\mathbf{d}})} \\ &= \frac{\partial[\mathbf{r}\mathbf{r}^H - \mathbf{r}^H \mathbf{A}\hat{\mathbf{d}} - \hat{\mathbf{d}}\mathbf{A}^H \mathbf{r} - \hat{\mathbf{d}}^H \mathbf{A}^H \mathbf{A}\hat{\mathbf{d}}]}{\partial(\hat{\mathbf{d}})} \\ &= \mathbf{0} - \mathbf{A}^H \mathbf{r} - \mathbf{A}^H \mathbf{r} - [\mathbf{A}^H \mathbf{A} + (\mathbf{A}^H \mathbf{A})^H]\hat{\mathbf{d}} \\ &= -2\mathbf{A}^H (\mathbf{r} - \mathbf{A}\hat{\mathbf{d}}) \end{aligned} \tag{16}$$

The superscript H is complex-conjugate (Hermitian) transpose. By substituting (16) into (15):

$$\frac{\partial \mathbf{q}}{\partial(\hat{\mathbf{d}})} = -2\mathbf{A}^H (\mathbf{r} - \mathbf{A}\hat{\mathbf{d}}) = \mathbf{0} \tag{17}$$

Therefore, the detection data of ZF-BLE is:

$$\hat{\mathbf{d}}_{ZF-BLE} = (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{r} = \mathbf{d} + (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{n} \tag{18}$$

From (18), the zero-forcing (ZF) equalizer applies the inverse of the system matrix to separate the user signals and eliminate multi-access interference (MAI). This scheme is very popular and is considered for the early TD-SCDMA demos. A Minimum-Mean Square Error (MMSE) detector minimizes the error between the weighted received signal and the desired bits, which can result in lower BER at high SNR levels. The computational costs of the ZF equalizer are smaller than that for the MMSE detector because the latter requires an estimate of the noise covariance matrix; however, the implementation issues are very similar in the circumstance of using smart aerial. This paper only addresses the zero-forcing detector.

3.2. Perturbation of Zero Forcing Block Linear Equalizer

To implement joint detection method, it is necessary to determine the system matrix $\mathbf{A}$. Usually, the accuracy of system matrix $\mathbf{A}$ is affected by the estimation CIRs. Strictly, the midamble would interfere with each of the adjacent data block after transmission and result an additional interference term. It is clearly found from(12) that the estimated CIRs have error compared with the real ones. The higher the noise remains in the channel estimation, the lower the accuracy of the estimated CIR can be achieved. Here, we use $\mathbf{\Delta}^{(k)} = (\Delta_1^k, \Delta_2^k, \cdots, \Delta_W^k)^T$ to build a bridge between the accuracy channel response $\mathbf{h}^{(k)} = (h_1^k, h_2^k, \cdots, h_W^k)^T$ and the estimated ones $\hat{\mathbf{h}}^{(k)} = (\hat{h}_1^k, \hat{h}_2^k, \cdots, \hat{h}_W^k)^T$, that is

$$\mathbf{h}^{(k)} = \hat{\mathbf{h}}^{(k)} + \mathbf{\Delta}^{(k)} \tag{19}$$

The combined CIR of the kth user can be rewritten as:

$$\mathbf{b}^{(k)} = \mathbf{h}^{(k)} * \mathbf{c}^{(k)} = (\hat{\mathbf{h}}^{(k)} + \mathbf{\Delta}^{(k)}) * \mathbf{c}^{(k)} = \hat{\mathbf{h}}^{(k)} * \mathbf{c}^{(k)} + \mathbf{\Delta}^{(k)} * \mathbf{c}^{(k)} = \hat{\mathbf{b}}^{(k)} + \boldsymbol{\xi}^{(k)} \tag{20}$$

Where $\boldsymbol{\xi}^{(k)}$ is resulted errors and has the same structure as $\hat{\mathbf{b}}^{(k)}$. Because the system matrix $\mathbf{A}$ is constructed according to $\hat{\mathbf{b}}^{(k)}$, it has the form resemble equation.

$$\mathbf{A} = \hat{\mathbf{A}} + \boldsymbol{\xi} \tag{21}$$

$\boldsymbol{\xi}$ is the error of system matrix which results from channel response errors $\mathbf{\Delta}^{(k)} = (\Delta_1^k, \Delta_2^k, \cdots, \Delta_W^k)^T$, it has the similar structure as $\mathbf{A}$.

Zero forcing block linear equalizer is based on least squares (LS) criterion. However, the least squares solution is vulnerable to the interference or error. Then, we give an analysis for perturbation of least squares.

Let $\mathbf{A}^\dagger$ is the pseudo-inverseof $\mathbf{A}$ and $\hat{\mathbf{r}} = \mathbf{r} - \mathbf{n}$. The solution $\hat{\mathbf{d}}_{ZF} = \mathbf{A}^\dagger \mathbf{r}$ is perturbed to $\hat{\mathbf{d}}_{ZF} + \delta\hat{\mathbf{d}}_{ZF} = \mathbf{A}^\dagger \hat{\mathbf{r}}$, and the residual $\boldsymbol{\zeta} = \mathbf{r} - \mathbf{A}\mathbf{d}_{ZF}$ to $\boldsymbol{\varepsilon} + \delta\boldsymbol{\varepsilon} = \hat{\mathbf{r}} - \mathbf{A}\mathbf{d}$. Let κ denote the spectral condition number $\kappa = \left\|\hat{\mathbf{A}}\right\|^2 \left\|\hat{\mathbf{A}}^\dagger\right\|^2$ and take $\varepsilon = \|\boldsymbol{\xi}\|^2 \left\|\hat{\mathbf{A}}\right\|^2$ and $\mathbf{y} = \hat{\mathbf{A}}^{\dagger H} \mathbf{d}_{ZF} = (\hat{\mathbf{A}}\hat{\mathbf{A}}^H)^\dagger \mathbf{r}$.

The following theorem gives bounds on $\left\|\delta\hat{\mathbf{d}}_{ZF}\right\|$ [28, 29].

Theorem: Assume that $rank(\mathbf{A}) = rank(\hat{\mathbf{A}})$, and $\kappa\varepsilon < 1$. Then:

$$\delta x_{LS} \le \frac{\kappa}{(1-\kappa\varepsilon)\left\|\hat{\mathbf{A}}\right\|^2} \left(\varepsilon \left\|\hat{\mathbf{d}}_{ZF}\right\|^2 \left\|\hat{\mathbf{A}}\right\|^2 + \|\mathbf{n}\|^2 + \kappa\varepsilon \|\boldsymbol{\zeta}\|^2\right) + \varepsilon \|\mathbf{y}\|^2 \left\|\hat{\mathbf{A}}\right\|^2 \tag{22}$$

NOTE. The last term of (22) vanishes if $rank(\hat{\mathbf{A}}) = rank(\mathbf{A})$, and $\left\|\hat{\mathbf{A}}^\dagger\right\|^2 \|\boldsymbol{\xi}\|^2 < 1$. Then:

$$\delta\hat{\mathbf{d}}_{ZF} \le \frac{\kappa}{(1-\kappa\varepsilon)\left\|\hat{\mathbf{A}}\right\|^2} \left(\varepsilon \left\|\hat{\mathbf{d}}_{ZF}\right\|^2 \left\|\hat{\mathbf{A}}\right\|^2 + \|\mathbf{n}\|^2 + \kappa\varepsilon \left\|\hat{\mathbf{A}}\right\|^2\right) \tag{23}$$

PROOF. From the decomposition theorem, $\hat{\mathbf{d}}_{ZF} = \hat{\mathbf{A}}^\dagger \mathbf{r}$ and $\hat{\mathbf{d}}_{ZF} + \delta\hat{\mathbf{d}}_{ZF} = \mathbf{A}^\dagger \hat{\mathbf{r}}$, it is seen that:

$$\delta\hat{\mathbf{d}}_{ZF} = \mathbf{A}^\dagger \hat{\mathbf{r}} - \hat{\mathbf{A}}^\dagger \mathbf{r} = (\mathbf{A}^\dagger - \hat{\mathbf{A}}^\dagger)\mathbf{r} + \mathbf{A}^\dagger \mathbf{n} = (-\mathbf{A}^\dagger \boldsymbol{\xi} \hat{\mathbf{d}}_{ZF} + \mathbf{A}^\dagger \boldsymbol{\zeta} + \mathbf{A}^\dagger \mathbf{n}) - P_{N(\mathbf{A})} \hat{\mathbf{d}}_{ZF} \tag{24}$$

where the first part belongs to $R(\mathbf{A})$ and the second belongs to $N(\mathbf{A})$.

$$\left\|\mathbf{A}^{\dagger}\xi\hat{\mathbf{d}}_{ZF}\right\| \le \left\|\mathbf{A}^{\dagger}\right\|^2 \left\|\xi\right\|^2 \left\|\hat{\mathbf{d}}_{ZF}\right\|^2 \le \frac{\left\|\mathbf{A}^{\dagger}\right\|^2}{1-\kappa\varepsilon}\left\|\xi\right\|^2 \left\|\hat{\mathbf{d}}_{ZF}\right\|^2 = \frac{\kappa\varepsilon}{1-\kappa\varepsilon}\left\|\hat{\mathbf{d}}_{ZF}\right\|^2 \tag{25}$$

$$\left\|\mathbf{A}^{\dagger}\zeta\right\| \le \left\|\mathbf{A}^{\dagger}\right\|^2 \left\|\xi\right\|^2 \left\|\zeta\right\|^2 \le \frac{\left\|\mathbf{A}^{\dagger}\right\|^2}{1-\kappa\varepsilon}\left\|\xi\right\|^2 \left\|\zeta\right\|^2 \le \frac{\kappa^2\varepsilon}{1-\kappa\varepsilon}\frac{\left\|\zeta\right\|^2}{\left\|\hat{\mathbf{A}}\right\|^2} \tag{26}$$

$$\left\|\mathbf{A}^{\dagger}\delta b\right\| \le \left\|\mathbf{A}^{\dagger}\right\|^2 \left\|\mathbf{n}\right\|^2 \le \frac{\kappa}{1-\kappa\varepsilon}\frac{\left\|\mathbf{n}\right\|^2}{\left\|\hat{\mathbf{A}}\right\|^2} \tag{27}$$

$$\left\|P_{N(\mathbf{A})}\hat{\mathbf{d}}_{ZF}\right\| = \left\|(\mathbf{I}-\mathbf{A}^H\mathbf{A}^{H\dagger})\hat{\mathbf{A}}^{\dagger}\hat{\mathbf{A}}\hat{\mathbf{A}}^{\dagger}\mathbf{r}\right\| = \left\|(\mathbf{I}-\mathbf{A}^H\mathbf{A}^{H\dagger})\hat{\mathbf{A}}^{H}\hat{\mathbf{A}}^{\dagger H}\mathbf{r}\right\| \le \left\|\xi\right\|^2 \left\|\hat{\mathbf{A}}^{\dagger H}\hat{\mathbf{d}}_{ZF}\right\| = \left\|\xi\right\|^2 \left\|\mathbf{y}\right\| \tag{28}$$

And arrive at inequality (22) from the expression for $\delta\hat{\mathbf{d}}_{ZF}$. Where $R(A)$ is subspace A matrix, $N(A)$ is Null space A matrix, $\left\|\bullet\right\|$ denotes the Frobenius norm of a matrix.

When $\xi = \mathbf{0}$ and $\mathbf{n}$ is a zero mean white Gaussian noise vector, $\hat{\mathbf{d}}_{ZF}$ has zero bias. It is also the maximum-likelihood estimator. When $\xi \ne \mathbf{0}$, $\hat{\mathbf{d}}_{ZF}$ will be biased in general, and will exhibit a pool performance. It suffers from perturbation of noise errors and increase covariance due to the accumulation of interference in $\mathbf{A}^H\mathbf{A}$.

3.3. Effect of Channel Estimation Error on ZF-BLE

In [28], authors analyze the effect of channel estimation errors on joint detection algorithms in TD-SCDMA system. Usually, the error is caused by the noise in the channel and the interference from adjacent cells.

Based on the above description, equation (18) can be rewritten as the following:

$$\hat{\mathbf{d}}_{ZF-BLE} = [(\hat{\mathbf{A}}+\xi)^H(\hat{\mathbf{A}}+\xi)]^{-1}(\hat{\mathbf{A}}+\xi)^H\mathbf{r} \tag{29}$$

In general, ξ is much smaller than system matrix $\hat{\mathbf{A}}$. Let $\hat{\mathbf{A}}^{\dagger} = (\hat{\mathbf{A}}^H\hat{\mathbf{A}})^{-1}\hat{\mathbf{A}}^H$ and omit the higher second order term, equation (29) can be predigested:

$$\begin{aligned}\hat{\mathbf{d}}_{ZF-BLE} &= [(\hat{\mathbf{A}}+\xi)^H(\hat{\mathbf{A}}+\xi)]^{-1}(\hat{\mathbf{A}}+\xi)^H\mathbf{r}\\ &\approx (\mathbf{I}-(\hat{\mathbf{A}}^H\hat{\mathbf{A}})^{-1}\hat{\mathbf{A}}^H\xi)(\mathbf{d}+(\hat{\mathbf{A}}^H\hat{\mathbf{A}})^{-1}\hat{\mathbf{A}}^H\mathbf{n})\\ &= (\mathbf{I}-\hat{\mathbf{A}}^{\dagger}\xi)(\mathbf{d}+\hat{\mathbf{A}}^{\dagger}\mathbf{n})\\ &= \underbrace{diag(\mathbf{I}-\hat{\mathbf{A}}^{\dagger}\xi)\mathbf{d}}_{desired\ \ signal} + \underbrace{\overline{diag}(\mathbf{I}-\hat{\mathbf{A}}^{\dagger}\xi)\mathbf{d}}_{ISI\ \ and\ \ MAI} + \underbrace{(\mathbf{I}-\hat{\mathbf{A}}^{\dagger}\xi)\hat{\mathbf{A}}^{\dagger}\mathbf{n}}_{noise}\end{aligned} \tag{30}$$

The first term of the right hand in (30) represents the desired signals, while the second term represents ISI and MAI, the third term represents the noise, respectively. If $\hat{\mathbf{A}}^{\dagger}\xi = \mathbf{0}$, channel estimation errors have no influence on ZF-BLE. If $\hat{\mathbf{A}}^{\dagger}\xi$ is a diagonal matrix, then there is no ISI and MAI at the output of the detector. If $\hat{\mathbf{A}}^{\dagger}\xi$ is nonzero and non-diagonal, ISI and MAI appear, and noise is also added.

4. Joint Detection Based on TLS Criterion

4.1. TLS Formulation

In TD-SCDMA system, various key technologies are built on the basis of precise estimation of CIRs, so the existence of errors can seriously affect the system performance. When the system matrix $\mathbf{A}$ has perturbation due to channel estimation error, the expression in (5) can be rewritten as:

$$\mathbf{r}-\mathbf{n}=(\hat{\mathbf{A}}+\xi)\mathbf{d} \tag{31}$$

We consider the problem:

$$\min_{\hat{\mathbf{A}},\mathbf{n},\mathbf{d}}\|\xi\|+\|\mathbf{n}\| \qquad subject \quad to:(\mathbf{r}-\mathbf{n})\in Range(\hat{\mathbf{A}}+\xi) \tag{32}$$

It is well known that total least square is a technique for solving this problem [31].

The TLS solution has been known for some times, however a well known modern treatment is due to Golub and Van loan [18]. The TLS approach has been extensively used in variety of scientific disciplines such as automatic control, statistics, biology, medicine and image restoration [20]. TLS method will also be used in joint detection.

The problem described by (31) can be restated as:

$$(\mathbf{G}+\mathbf{D})\mathbf{z}=\mathbf{0}. \tag{33}$$

Where $\mathbf{G}=[\mathbf{A}\,|\,\mathbf{r}]$ is augmented matrix, $\mathbf{D}=[\xi\,|\,\mathbf{n}]$ is perturbation matrix, vector $\mathbf{z}=[\mathbf{d},-1]^T$. Mathematically, its solution can be found using the criterion of total least squares (TLS). Solving the homogeneous (33) the general least squares (TLS) can be expressed as the constraint optimization problem:

$$\min\|\mathbf{D}\| \;\; subject \;\; to \;\; (\mathbf{G}+\mathbf{D})\mathbf{z}=0 \tag{34}$$

In [18], Golub and Van loan showed an efficient and reliable numerical algorithm to compute the TLS solution. The TLS solution is related to the right singular vector of $\mathbf{G}$ associated with the smallest singular value. The singular value decomposition (SVD) of matrix $\mathbf{G}$ can be written as:

$$\mathbf{G}=\mathbf{U}\boldsymbol{\Sigma}\mathbf{V}^H \tag{35}$$

Let λ_i, $\mathbf{u}_i$, $\mathbf{v}_i$ be the ith singular value, left singular vector, and right singular vector of $\mathbf{G}$, respectively. They are related by:

$$\mathbf{G}\mathbf{v}_i=\lambda_i\mathbf{u}_i \;\; and \;\; \mathbf{G}\mathbf{u}_i=\lambda_i\mathbf{v}_i \tag{36}$$

The $\mathbf{v}_{n+1}$ is the right singular vector corresponding to the smallest singular value of $\mathbf{G}$, and then, the vector $[\mathbf{x}_{TLS}^T,-1]^T$ is parallel to the right singular vector. The TLS solution is obtained from:

$$\begin{bmatrix}\mathbf{x}_{TLS}\\-1\end{bmatrix}=-\frac{\mathbf{v}_{n+1}}{v_{n+1,n+1}} \tag{37}$$

Where $v_{n+1,n+1}$ is the last component of $\mathbf{v}_{n+1}$.

In some case, TLS problem may have no a solution. In other case, TLS problem may lack a unique solution. However, whenever this is the case, it is possible to single out a unique "minimum norm" TLS solution.

4.2. Conjugate Gradient Algorithm for Total Least-Squares

It has been shown that the constrained minimization problem in (34) is equivalent to the following Rayleigh quotient minimization problem:

$$\min F(\mathbf{z}) = \frac{\mathbf{z}^H \mathbf{G}^H \mathbf{G}\mathbf{z}}{\mathbf{z}^H \mathbf{z}} \tag{35}$$

Which in turn is equivalent to finding the eigenvector $\mathbf{z}$ associated with the smallest eigenvector of $\mathbf{G}^H\mathbf{G}$. The function $F(\mathbf{z})$ is the Rayleigh quotient. The minimal value of $F(\mathbf{z})$ is in fact equal to the minimal perturbation that satisfies Equation (31).

A recursive TLS algorithm was first used by minimizing the Rayleigh quotient [32]. In general, the SVD-based TLS algorithm can become computationally prohibitive for large-scale systems, because this algorithm needs a large number of multiplications. The conjugate gradient CG method converges very fast and is particularly used to handle large matrices.

The CG method begins with $\mathbf{z}(0)$ and updates $\mathbf{z}(k)$ by recurrence formula:

$$\mathbf{z}(k+1) = \mathbf{z}(k) + \alpha(k)\mathbf{p}(k) \tag{36}$$

Where $\alpha(k)$ is chosen to reach the minimum of $F(\mathbf{z})$ in the direction $\mathbf{p}(k)$. $\alpha(k)$ is satisfied with the (37):

$$D[\alpha(k)]^2 + B[\alpha(k)] + C = 0 \tag{37}$$

Among the two possible solutions of (37), the one that yields the smaller value of $F(\mathbf{z})$ is given by:

$$\alpha(k) = \pm\frac{1}{2D}(-B + \sqrt{B^2 - 4CD}) \tag{38}$$

Plus sign is suitable for minimum update, and minus is suitable for maximum update.
Where:

$$D = P_b(k)P_c(k) - P_a(k)P_d(k) \tag{39}$$

$$B = P_b(k) - \lambda(k)P_d(k) \tag{40}$$

$$C = P_a(k) - \lambda(k)P_c(k) \tag{41}$$

$$P_a(k) = \langle \mathbf{Gz}(k), \mathbf{Gp}(k)\rangle \tag{42}$$

$$P_b(k) = \langle \mathbf{Gp}(k), \mathbf{Gp}(k)\rangle \tag{43}$$

$$P_c(k) = \langle \mathbf{z}(k), \mathbf{q}(k)\rangle \tag{44}$$

$$P_d(k) = \langle \mathbf{p}(k), \mathbf{p}(k)\rangle \tag{45}$$

$$\lambda(k) = \langle \mathbf{Gz}(k), \mathbf{Gz}(k)\rangle \tag{46}$$

At $(k+1)th$ time the new search direction is chosen as:

$$\mathbf{p}(k+1) = \mathbf{r}(k+1) + \beta(k)\mathbf{p}(k) \tag{47}$$

and the residue $\mathbf{r}(k+1)$ is given by:

$$\mathbf{r}(k+1) = \lambda(k)\mathbf{z}(k+1) - \mathbf{G}^H\mathbf{G}\mathbf{z}(k+1) \tag{48}$$

The $\beta(k)$ is conjugate gradient parameter, to make the direction vectors $\mathbf{p}(k)\mathbf{G}^H\mathbf{G}$-conjugate, *i.e.*

$$\langle \mathbf{G}^H\mathbf{G}\mathbf{p}(k), \mathbf{p}(k+1)\rangle = 0 \tag{49}$$

The convergence criterion that we use is:

$$\left|\frac{\lambda(k+1)-\lambda(k)}{\lambda(k)}\right|<\varepsilon \quad (50)$$

Where ε is the error bound. The initial solution $\mathbf{z}(0)$ is set to a vector in which all elements except the last come from $\hat{\mathbf{d}}_{ZF-BLE}$ and the last element is set to 1.

The $\beta(k)$ is given as:

$$\beta_k^{FR}=\frac{\|\mathbf{r}(k+1)\|^2}{\|\mathbf{r}(k)\|^2} \quad (51)$$

This method was developed by Fletcher Reeves (FR) [33], and was also described by Yang [34].

Some other well-known conjugate gradient methods include the Hestenes Stiefel method (HS)[35], the Polak Ribiere Polyak method (PR) [36] and the Dai Yuan method (DY) [37].

The difference of these methods is parameter $\beta(k)$, the parameters $\beta(k)$ of these methods are specified as follows:

$$\beta_k^{HS}=\frac{\mathbf{r}(k+1)^H(\mathbf{r}(k+1)-\mathbf{r}(k))}{\mathbf{p}(k)^H(\mathbf{r}(k+1)-\mathbf{r}(k))} \quad (52)$$

$$\beta_k^{PR}=\frac{\mathbf{r}(k+1)^H(\mathbf{r}(k+1)-\mathbf{r}(k))}{\|\mathbf{r}(k)\|^2} \quad (53)$$

$$\beta_k^{DY}=\frac{\|\mathbf{r}(k)\|^2}{\|\mathbf{p}(k)^H(\mathbf{r}(k+1)-\mathbf{r}(k))\|^2} \quad (54)$$

The dominating operations during an iteration of CG are matrix-vector products. The conjugate gradient CG method usually requires $O(n^2)$ multiplications per iteration [38]. However, it is well known that the CG method converges very fast and is particularly suitable for large matrices.

5. Simulation Result And Analysis

To compare the ZF-BLE and TLS approaches, computer simulation has been carried out to evaluate the performance of the proposed algorithm by this paper.

5.1. Simulation Parameter

In order to evaluate the performance of the proposed algorithm, computer simulation has been carried out to evaluate the performance of the proposed algorithm by this paper. The TD-SCDMA parameters used in our simulations are listed in Table 1 and all the datum have been conducted according to 3GPP specifications.

Table 1. Simulation Parameters

Chip Rate	1.28 Mcps
Modulation	QPSK
User data rate	12.2kbps
Channel length (W)	16 chips
Active users per slot (K)	8users
Interfering users	4users
Carrier frequency	2.0GHz
Effective training sequence length (P)	128 chips
Spreading factor (Q_k)	16 for each user
RRC roll-off factor	0.22

The wireless fading channel is vehicular environment, $v = 120km/h$, which derived from the CATT (Chinese Academy of Telecommunication Technology) channel models. It is a four-path Rayleigh fading channel, with average power of (0, -3, -6, -9 dB) and relative delay of (0, 781, 1563, 3125 ns). The simulation datum comes from the collected test cases datum in the technical specification of 3GPP TS34.122.

From the above the parameter of system and channel model, multiple access interference (MAI) and inter-symbol interference (ISI) are the main interference to the TD-SCDMA system. The error is inevitable in the channel estimation matrix.

5.2. Performance Comparison

In order to clearly compare the performance of ZF-BLE and the different conjugate gradient algorithms, we give the results of two scenarios. One is 8 users which occupy 10 code-channels, and another is 8 users which occupy full code-channel. In Figure.3 and 4, different algorithms are compared in terms of the BER performance on 10 code-channel scenario, respectively for the iteration number 5 and 10. Figure.5 compares the BER performance of different algorithms on full code-channel scenario, based on the error bounds, $\varepsilon = 10^{-4}$. The three figures show that the BER gets lower as the Signal to Noise Ratio gets higher. But under the same SNR, the BER of proposed method is lower than that from the ZF-BLE method. The performance of different CG algorithms is almost no difference. The FR algorithm is slightly worse, because its convergence is slow.

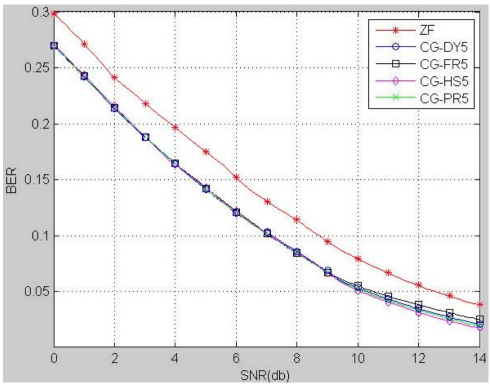


Figure 3. Comparison of BER Performance of Different Algorithm in 10 Code-Channel Scenario for the Iteration Number 5

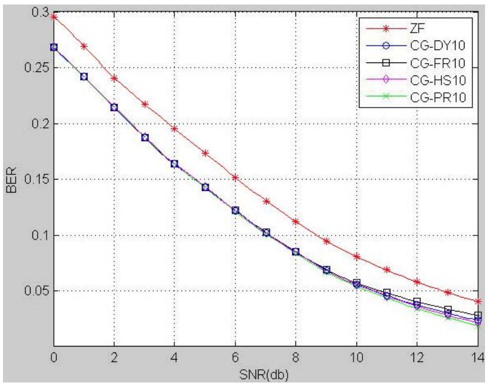


Figure 4. Comparison of BER Performance of Different Algorithm in 10 Code-Channel Scenario for the Iteration Number 10

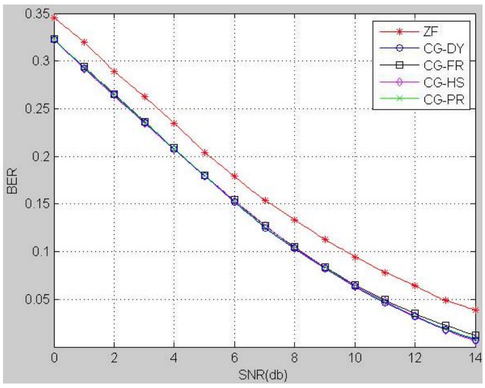


Figure 5. Comparison of BER Performance of Different Algorithm in Full Code-Channel Scenario for Error Bounds $\varepsilon = 10^{-4}$

5.3 Convergence Analysis

Because the proposed method is iteration algorithm, the convergence analysis is important. In general, the conjugate gradient method is used for large matrix, which is not feasible to run a large number of iterations.

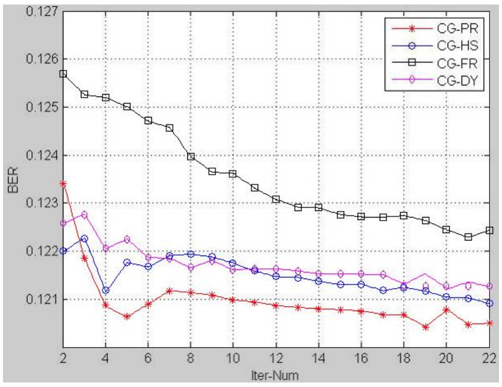


Figure 6. Curve of BER in 10 Code-Channel under Different the Number of Iteration, in SNR=5

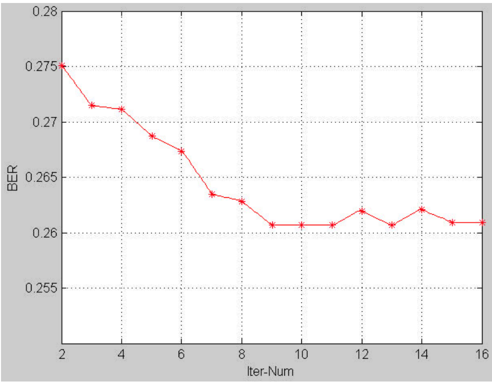


Figure 7. BER Performance under Different the Number of Iteration, in SNR=2

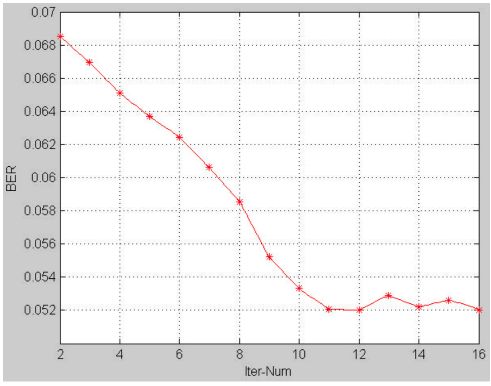


Figure 8. BER Performance under Different the Number of Iteration, in SNR=11

In Figure.6, it shows that the BER performance of four CG methods for 8 users with 10 code-channels, in SNR=5. The fluctuation of performance became weaker with the iteration number. After about 10 times iteration, the CG method can reach a stable-value of BER. In Dai-Yuan method as an example, the curve of convergence is demonstrated in Figure.7 and Figure.8, at SNR=2 and SNR=11. We can get the same conclusion from the both figures.

6. Conclusion

In this paper, an iterative TLS algorithm employing a CG method is proposed for joint detection of TD-SCDMA downlink in fast time-varying channels. It is suitable for multi-user systems. Compared with ZF-BLE, when the channel estimation has error, the proposed method outperforms the ZF-BLE. To illustrate the application of the proposed technique, simulated data come from TD-SCDMA system. In the future, another way to improve the stability and the speed in solving the perturbation problem is by using a wavelet transform. We are also investigating how to improve the robustness of the TLS solution.

References

[1] G. Liu, J. Zhang, P. Zhang, Y. Wang, X. Liu, S. Li, Evolution map from TD-SCDMA to future B3G TDD. IEEE Commun. Mag. 44(3), 54–61 (2006).
[2] A. J. Paulraj, B. Papadias, Space-time processing for wireless communications, IEEE Signal Processing Magazine, pp. 49-83, 1997,11.
[3] N. W. Anderson, H. R. Karimi, and P. Mangold, "Software-Definable Implementation of a TDMA/CDMA Transciever," Proc. of ICSPAT, 1998.
[4] M. Vollmer, M. Haardt, J. Gotze, "Comparative Study of Joint-Detection Techniques for TD-CDMA Based Mobile Radio Systems", IEEE J. Selected Areas of Communications, pp. 1461-1475, Aug. 2001.
[5] A. Klein, G. K. Kaleh, and P. W. Baier, "Zero Forcing and Mnimum Mean-Square-Error Equalization for Multiuser Detection in Code-Division Multiple-Access Channels", IEEE Transactions on Vehicular Technology, Vol. 45, No. 2, May 1996.
[6] N. Benvenuto and G. Sostrato, "Joint Detection with Low Computational Complexity for Hybrid TD-CDMA Systems", IEEE Journal on Selected Areas in Communications, Vol. 19, No. 1, Jan. 2001.
[7] J. Blanz, A. Klein, M. Na han,, "Performance of a Cellular Hybrid C/TDMA Mobile Radio System Applying Joint Detection and Coherent Receiver Antenna Diversity". IEEE Journal on Selected Areas in communications, pp.568-579, 1994, 12(4).
[8] A. J. Paulraj, B. Papadias, "Space-time processing for wireless communications", IEEE Signal Processing Magazine, pp. 49-83, 1997,11.
[9] SEE C S, COWAN C F N, NEHORAI A. Spatiotemporal channel identification and Equalization in the presence of strong Co- channel interference [J].Signal Processing, 1999, 78:127- 138.
[10] B. Steiner, P. Baier. Low cost channel estimation in the uplink receiver of CDMA mobile radio systems [J]. Frequen, 1993, 47 (12): 292-298.
[11] B. Steiner, P. Jung. Optimum and suboptimum channel estimation for the uplink of CDMA mobile radio systems with joint detection [J]. European Trans. on Telecommunications, 1994, 5(1): 39-50.
[12] Kang Shao-li, Qiu Zheng-ding, Li Shi-he. Improvement of the low-cost channel estimation method used in TD-SCDMA system [J]. Journal on Communications, 2002, 23(10):108-113.
[13] Chang Yong-yu, Huang Li-li Yang Da-cheng. Performance analysis improvement of the channel estimation algorithm in the TD-SCDMA system [J]. Journal of Electronics & Info Technology, 2005, 27(7):1110-1113.
[14] Xiaoqin Song , Ke Li, Ping Song, Zhijian Shen. Joint channel estimation algorithm for intra-frequency TD-SCDMA system. IEEE Int. Conference Neural Networks & Signal Processing. Zhenjiang, China, June 8~10, 2008. Pp:461-465.
[15] Weifeng Cao, Xiaohui Yu, Wenbo Wang, "A novel channel estimation algorithm with PN training sequence in TD-SCDMA systems," Communications, Circuits and Systems, 2004, vol.2, pp.847-850.
[16] Xiaoqin Song, Ke Li, "Improved channel estimation algorithm based on parallel interference cancellation," Neural Networks and Signal Processing, 2008, pp.466-469.
[17] Ali K. Marzook, A. Ismail, B. M. Ali, A. Sali, S. Khatun. "Singular value decomposition rank-deficient-based estimators in TD-SCDMA systems," Circuits, Systems, and Signal Processing. February 2013, Volume 32, Issue 1, pp: 205-221.
[18] G. H. Golub and C. F. Van Loan, "An analysis of the total least squares problem," SIAM J. Numer. Anal., vol. 17, no. 6, pp. 883-893, Dec. 1980.
[19] N.H. Younan and X. Fan, "Signal restoration via the regularized constrained total least squares", Signal Processing Volume 71, Issue 1, 30 November 1998, Pages 85-93.
[20] Amir Beck and Aharon Ben-Tal. on the solution of the tikhonov regularization of the total least squares problem,. Vol. 17, No. 1, pp. 98–118 SIAM J. OPTIM. 2006
[21] S. V. Huffel and J. Vande walle, The Total Least-Squares Problem. Philadelphia, PA: SIAM, 1991.
[22] Zhu, W., Wang, Y., Yao, Y., Chang, J., Graber, H., and Barbour, R., 1997, Iterative total least squares image reconstruction algorithm for optical tomography by the conjugate gradient method: J. Opt. Soc. Am. A, 14, no. 4, 799–807. J. Name Stand. Abbrev., in press.

[23] H. Chen, T. K. Sarkar, S. A. Dianat, and J. D. Brule, ‘‘Adaptive spectral estimation by the conjugate gradient method,’’ IEEE Trans. Acoust. Speech Signal Process. ASSP-34, 272–284 (1986).
[24] X. Yang, T. K. Sarkar, and E. Arvas, ‘‘A survey of conjugate gradient algorithms for solution of extreme eigenproblem of a symmetric matrix,’’ IEEE Trans. Acoust. Speech Signal Process. 37, 1550–1556 (1989).
[25] A. Papathanassion, J. Oster and P. WBaiser, ‘‘A Novel Simulation Concept of Reduced Computational Cost for TD-CDMA Mobile Radio Systems with Adaptive Antennas’’, Proc. IEEE 50th Vehicular Technology Conference (VTC’99 Fall), pp.218-222, Amsterdam, 1999.
[26] 3GPP TS 25.221, V7.4.0, Physical channels and mapping of transport channels onto physical channels (TDD), Sept., 2007.
[27] A. Klein, G. K. Kaleh, and P. W. Baier, “Zero Forcing and Mnimum Mean-Square-Error Equalization for Multiuser Detection in Code-Division Multiple-Access Channels”, IEEE Transactions on Vehicular Technology, Vol. 45, No. 2, May 1996.
[28] Per-Å ke Wedin, perturbation theory for pseudo inverses, BIT, 13(1973), 217-232
[29] TL. Fan, HW. Wu, HC. Huang. Channel Estimation and Interference Cancellation for OFDM Systems Based on Total Least Squares Solution. JOURNAL OF COMMUNICATIONS, VOL. 6, NO. 8, NOVEMBER 2011, pp:640-647
[30] KANG Shao-li, QIU Zheng-ding, LI Shi-he. The effect of channel estimation errors on joint detection algorithms in TD-SCDMA System. International Conferences on Volume 2, Issue , 2001 Page(s):303 - 308 vol.2
[31] TL Fan, YC Wen, A novel equalization Technique for high mobility OFDM system. PIAGENG 2013: Proc. of SPIE Vol. 8762 87621N-2
[32] C. E. Davila, ‘‘An efficient recursive total least squares algorithm for FIR adaptive filtering,’’ IEEE Trans. Signal Process. 42, 268–280 (1994).
[33] R. Fletcher and C. M. Reeves, ‘‘Function minimization by conjugate gradients,’’ Comput. J. 7, 149–154 (1964).
[34] X. Yang, T. K. Sarkar, and E. Arvas, ‘‘A survey of conjugate gradient algorithms for solution of extreme eigen-problem of a symmetric matrix,’’ IEEE Trans. Acoust. Speech Signal Process. 37, 1550–1556 (1989).
[35] M.R.Hestenes, E.L.Stiefel, Methods of conjugate gradients for solving linear systerm, Journal of Research of the National Bureau of Standards，Vol.49,pp409-432,1952.
[36] Polyak B T. The conjugate gradient method in extreme problems [J]. USSR Computation Math and Math Physics，1969，9(4)：94-112.
[37] Dai Yuhong，Yuan Yaxiang. A nonlinear conjugate gradient method with a strong global convergence property [J]. SIAM Journal on Optimization，1999，10(1)：177-182.
[38] Shewchuk J R. An Introduction to the Conjugate Gradient Method Without the Agonizing Pain. 1994

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