Abstract— Code Division Multiple Access (CDMA) is a channel access method, based on spread-spectrum technology, used by various radio technologies world-wide. In general, CDMA is used as an access method in many mobile standards such as CDMA2000 and WCDMA. We address the problem of blind multiuser equalization in the wideband CDMA system, in the noisy multipath propagation environment. Herein, we propose three new blind receiver schemes, which are based on state space structures and Independent Component Analysis (ICA). These blind state-space receivers (BSSR) do not require knowledge of the propagation parameters or spreading code sequences of the users—they primarily exploit the natural assumption of statistical independence among the source signals. We also develop three semi-blind adaptive detectors by incorporating the new adaptive methods into the standard RAKE receiver structure. Extensive comparative case-study, based on Bit error rate (BER) performance of these methods, is carried out for different number of users, symbols per user, and signal to noise ratio (SNR) in comparison with conventional detectors, including the Blind Multiuser Detectors (BMUD) and Linear Minimum mean squared error (LMMSE). The results show that the proposed methods outperform the other detectors in estimating the symbol signals from the received mixed CDMA signals. Moreover, the new blind detectors mitigate the multi access interference (MAI) in CDMA.

Keywords— Blind Multiuser Detection (BMUD), Fast Fixed-Point independent component algorithm (FastICA), Robust independent component algorithm (RobustICA), Direct-Sequence CDMA (DS-CDMA), Wide-band CDMA (W-CDMA), Linear Minimum mean squared error (LMMSE), Multi Access Interference (MAI), Principle Component Analysis (PCA).

I. INTRODUCTION

Code Division Multiple Access (CDMA) is a channel access method used by various radio technologies. It is based on spread-spectrum technology such as is found in third-generation (3G) cellular telephony, terrestrial and satellite communications systems, and indoor wireless networks [1-2], [9]. Although, LTE (4G) is utilized in many cellular companies inside and outside the U.S., the networks are still not fully built out, and LTE coverage is still not universal. Thus, most of the older 2G and 3G systems are still in charge or at least working in parallel with the 4G. For example, in U.S. companies, AT&T and T-Mobile use GSM/WCDMA/HSPA while Verizon, Sprint, and MetroPCS use cdma2000/EV-DO [3-5]. Moreover, the LTE wireless interface is incompatible with 2G and 3G networks, so that it must be operated on a separate wireless spectrum. 3G is intended to be replaced by 4G technologies sooner or later, but it is going to take a long time before LTE coverage is developed so fully as to be fully operational and universal, especially in some countries worldwide, such as India, Iraq … etc. [26-27].

As with any radio communication system, CDMA systems are considered as interference-limited; they suffer from different types of interference, namely an internal multiple access interference (MAI) due to the non-ideal cross-correlations between users’ spreading sequences, narrow-band interference, inter-symbol interference (ISI) and noise at the receiver. These drawbacks, in general, affect the performance of a CDMA system. In highly loaded systems, conventional detectors are considered an unsuitable choice. Most of them suffer from external interference sources, such as adjacent channel interference or jamming, and treat the interference as an additional background noise. Specifically, the primary source of interference is MAI in the CDMA system. This has motivated the development of numerous interference rejection techniques to overcome the MAI and the near-far problem in the conventional receiver. Several state-of-the-art approaches have been proposed in literature to overcome this challenge, such as trained-based systems. Also, the most conventional detection for the CDMA signals is based on the second order statistics among user codes.

In the CDMA system, multiuser detection has been presented in several works in order to enhance channel capacity and mitigate multiple access interference (MAI). Multiuser detection was first established to obtain an optimum multiuser detector for multi-Gaussian channel in [1]. In addition, several suboptimum detectors have been proposed in [6-8], because of the computational complexity in the optimal detector which make it unrealistic. In [1] and [32-36], the training sequence techniques were used to present suboptimum detectors, i.e. an adaptive linear detector and zero-forcing detector. In [6], authors proposed a suboptimal detector based on the linear minimum mean square error (LMMSE) method.

In [8], X. Wang and H. Poor proposed the blind MMSE and the blind de-correlating detectors. In [31-36], adaptive blind detectors were proposed based on incorporating the
minimum output energy with constrained optimization methods. Several subspace approaches were proposed in the literature, i.e. [20], [20], [36]. In [10], several types of group-blind linear detectors were proposed in order to enhance the performance for uplink and downlink channels. The key idea of these detectors was to take advantage of the cross-correlation matrix which was constructed by exploiting the correlation between the successive received signals. These detectors are too complex to be implemented. Also, they require information regarding timing and the spreading waveform of the desired user.

The aforementioned techniques periodically require the user to send a training sequence that must be known by the receiver in order to enable the receiver to estimate the parameter of the propagation channel, which is caused by the multiple reflections of the radio waves on the obstacles encountered, i.e. buildings, cars, trees, etc. Furthermore, according to [42], it has been reported that 20% of the bandwidth is devoted to the training sequence in GSM and up to 40% in UMTS. In spite of the good performance of the aforementioned techniques, the cost tends to be significantly large in terms of bandwidth. However, adaptive signal processing techniques seem to be more sufficient methods for CDMA systems in the presence of high dynamic conditions due to the mobility of the mobile terminal, the short code case and the fortuitous channel access. In particular, attempts to ensure a high communication rate have made blind adaptive techniques a hot topic for the last decade, due to their potential to eliminate/reduce training sets. Also, blind techniques help to recover the signals in some other situations such as 1) eavesdropping, where using the training sequence is not possible or not available, 2) maintaining, when the receiver fails to keep the desired user on track. However, the underlying user symbol sequences are usually mutually independent. Therefore, independency is the key assumption that makes the CDMA system a suitable environment to take advantage of the blind techniques, such as information maximization [1] and minimum mutual information [6]. In [6-8], the CDMA system is an important area of the blind adaptive algorithm in terms of application, since a wide stationary slowly fading multipath CDMA environment can be expressed as a linear multi-channel convolution model. Thus, the received signals in the CDMA system can be considered as a sum of the non-Gaussian signals generated by the linear convolutive model of statistically independent components of users (as shown in [6], [10], [31-36]). Nevertheless, the adaptive LMMSE detector has been proposed to overcome the complex matrix inversion operation, but this detector still requires the spreading codes of all users. Therefore, the MMSE detector might not be realistic in the downlink receiver. Furthermore, it might be insecure in the downlink case. However, it seems more suitable to work in the uplink case. Therefore, this paper aims to recover the source symbol sequences from the linear convolutive received mixture without any knowledge of the user spreading codes and in the absence of channel identification. Simply put, this paper proposes blind adaptive detections, based on a state space approach using a natural gradient method for multipath channels in CDMA systems. Three update-laws are derived based on the state space structures and then three blind state-space receivers (BSSR) are developed for MAI, ISI suppression and symbol estimations. The second contribution of this paper is three semi-blind adaptive algorithms based on the corporation between the Rake receiver and the stochastic gradient algorithms which are used in several blind adaptive signal processing algorithms, namely FastICA, RobustICA, and principle component analysis PCA. Furthermore, one relatively new idea presented in this paper is to use and explore a higher order statistics (HOS) in order to make the methods robust and secure against incomplete cross-correlation and a near-far problem which considers other drawback factors in conventional detection methods. The simulations are carried out to study and verify the effectiveness of the proposed methods for solving the symbols estimations. Moreover, we observe variations in the bit error-rate as a function of the signal-to-noise ratio, number of users and number of symbols per user. Finally, a comparison is attempted between the proposed methods and conventional ones in terms of performance and their computational complexity.

Throughout this paper, lower case letters denote scalars, bold lower case letters denote vectors, and bold upper case letters denote matrices. The following symbols are used to present our work:

- $(\cdot)^T$ refers to transpose operator;
- $(\cdot)^H$ refers to Hermitian transpose operator;
- $\text{trace}(\cdot)$ refers to the trace operator.
- $j = \sqrt{-1}$ refers to the imaginary unite.
- $\text{diag}(\cdot)$ refers to diagonal matrix;
- $\text{sgn}(\cdot)$ refers to sign operator;
- $E[\cdot]$ refers to statistical expectation.

The remainder of the paper is organized as follows. In Section II, a brief description and derivation of synchronous CDMA signal models in multi-path fading are presented. The conventional receiver procedures are described in Section III. Section IV is dedicated to the derivation of adaptive updated laws and to a proposal regarding new detection schemes. The comparative simulations results and conclusion are given in Section V and Section VI, respectively.

## II. CDMA Signal Models

In this section, we briefly present the signal model for a CDMA implementation using one layer of spreading codes only. Next, we briefly describe the DS-CDMA signal and WCDMA signal models in a typical synchronous CDMA system employed for indoor ATM and certain ad hoc wireless networks [1], [3] as shown in Fig.1 and Fig. 2, respectively.

### A. DS-CDMA Receiver Signal Model

In a DS-CDMA system, several users share the medium simultaneously by using their own signatures. The simplest received signal model \( r(t) \) before filtering in a symbol interval is given by

\[
r(t) = \sum_{m=1}^{M} \sum_{k=1}^{K} \sum_{l=0}^{L} \alpha_{mn} b_{k,m} s_k(t - mT_b - d_i T_c) + n(t)
\]

(1)
where

- \( I, K, M \) are path, user and symbol indices, respectively.
- \( \alpha_{tm} \) is the path gain, since in the downlink model the path gain does not differ among users because all users’ signals are sent together and the path gain \( \alpha_{tm} \) and propagation delay factor \( d_t \) depend only on the number of paths.
- \( b_{k,m} \) is symbol.
- \( s_k(.) \) is spreading code (chip sequence).
- \( d_t \) is the propagation delay factor, \( d_k \in \{0, 1, ..., \frac{L-1}{2} \} \)
- \( C \) is the number of chips per symbol.
- \( T_b, T_c, t \) are time, symbol and chip duration, respectively.
- \( n(t) \) is an additive white Gaussian noise (AWGN) channel.

In this paper, the system is assumed to be time-invariant, which means that the channel parameters are much slower than the frequency of transmitted symbol data. However, let us assume that \( G \) is the number of code sequences, \( K \) is the number of users, and \( L \) is the number of channels. Thus, the vector form of the equation (1) will change to:

\[
\mathbf{r} = \mathbf{H} \mathbf{S} \mathbf{b} + \mathbf{n}
\]

(2)

Where \( \mathbf{r} \) is the received vector signal; \( \mathbf{H} \) is a \((G + L - 1) \times G \) matrix, which represents the multipath propagation coefficients; \( \mathbf{S} \) is a \( G \times K \) block diagonal matrix; \( \mathbf{b} \) is a \( K \times d \) vector, which represents the data symbols; and \( \mathbf{n} \) is the \((G + L - 1) \times d \) channel noise vector with covariance matrix \( \mathbf{Q} \). This model of received signals (2) is suitable for deriving the linear filters such as the MF, the RAKE, the blind LMMSE, and the blind detectors based on FastICA and Robust ICA algorithms. In addition, an alternative signal model, a linear convolutive model, is given by:

\[
\mathbf{r}_n = \mathbf{H}_0 \mathbf{b}_n + \mathbf{H}_1 \mathbf{b}_{n-1} + \mathbf{n}_n = \mathbf{H} \mathbf{b}_n + \mathbf{n}_n
\]

(3)

where

- \( \mathbf{r}_n \) is the received signal vector;
- \( \mathbf{b}_n = [b_1(n), ..., b_K(n)]^T \) is the current bits of all users;
- \( \mathbf{H}_0 = [\mathbf{h}_1, ..., \mathbf{h}_K] \) is the signature matrix of the current bits of all users including MAI;
- \( \mathbf{H}_1 = [\mathbf{h}_1, ..., \mathbf{h}_K] \) is the signature matrix of the previous bits of all users including ISI;
- \( \mathbf{n}_n = [n(nN), ..., n(nN + N - 1)]^T \) is the independent white Gaussian Noise vector.

In uplink (asynchronous) CDMA systems, one can assume that \( \mathbf{H}_0 \) and \( \mathbf{H}_1 \) are mutually independent; therefore, \( \mathbf{H} \) is a full column matrix and its rank is 2K. Whereas for downlink (synchronous) CDMA communication, \( \mathbf{H} \) is a matrix and its rank is full-rank with minimal restricted. The main focus in this paper is on the synchronous CDMA communication system, although our proposed algorithms also work well in the asynchronous CDMA system [10], [30].

B. WCDMA Receiver Signal Model

![Fig. 1. Signal generation model for a typical QPSK DS-CDMA system](image)

The difference between a WCDMA system and a DS-CDMA system is the presence of scrambling codes. The main reason behind the MAI in the WCDMA system is the cell multiple user signals sharing the same multipath channels. However, the simplest received signal model \( r(t) \) before filtering in a symbol interval is given by:

\[
r(t) = \sum_{m=1}^{M} \sum_{k=1}^{K} \sum_{l=0}^{L} a_{tm} b_{k,m} c_k (t - d_l T_c) s_k (t - m T_b - d_l T_c) + n(t)
\]

(6)

Where \( c_k(t) \in \{\pm 1 \pm j\} \) are the complex cell-specific scrambling sequences, the rest of the variables are defined in a similar manner to the model (1). The received signal at UE/MS is passed through a chip-matched filter and sampled at
chip rate. The received vector \( r \) in this case can be expressed as

\[
r = HCs_b + n
\]  

(7)

Where \( C \) is the \( G \times G \) complex diagonal scrambling matrix with \( C^H C = I_{G \times G} \) and the rest of the variables are defined as similar in (2). The form of \( C \) is given by:

\[
C = \text{diag}[c_1, c_2, \ldots , c_n]
\]  

(8)

Where

\[
c_i \in \{\pm 1 \} \quad \forall \; 1 \leq i \leq G
\]

![Fig. 2. Signal generation based on the proposed 3GPP UMTS FDD standard](image)

### III. CONVENTIONAL BLIND LINEAR MULTIUSER DETECTORS

In this section, we briefly describe the conventional linear multiuser detectors such as the Match Filter (MF), the Rake receiver and the LMMSE detector in multipath environment.

#### A. Single user detection (SUD) Detector

The SUD is a standard MF detector which exploits the user’s signatures to make the best estimation of the user’s sequences from the data received at MS. This detector completely ignores the MAI due to other users sharing the resources. One can express the MF Detector for \( ith \) user in DS-CDMA system as follows:

\[
b_{LMMSE}^D = S_i^H \hat{r}
\]  

(9)

where \( S_i \) is the estimated chip-rate user signature code matrix, \( \hat{r} \) is the received data, and \( b_{LMMSE}^D \) is the estimated DS-CDMA symbol vector.

#### B. Rake Detector

Perhaps, the most special case of linear multiuser detector is the Rake Detector, which consists of multiple chip-delayed SUD fingers in parallel. In this paper, we implement the Rake receiver with the knowledge of both channel delays and channel coefficients. However, one can express the RAKE for DS-CDMA system mathematically as follows:

\[
b_{RAKE}^D = S_i^H H_i \hat{r}
\]  

(10)

Where \( H \) is the estimated channel matrix, and \( b_{RAKE}^D \) is the estimated \( ith \) user’s symbol.

### C. LMMSE Detector

Despite the fact that the conventional linear detectors based on the Least Square (LS), Zero-Force (ZF) and BLUE algorithms perform poorly especially in colored noise presence, the LMMSE detector is considered one of the best linear detector for DS-CDMA system. However, one can express the LMMSE as follows:

\[
b_{LMMSE}^D = S_i^H H_i (\sigma^2 HH^H + Q)^{-1} \hat{r}
\]  

(11)

Where \( (\sigma^2 HH^H + Q) = R = E[rr^H] \) is the auto-correlation of the received data at the MS, and \( \sigma^2 \) is the average power of the transmitted power. There are several drawbacks in the implementation of the LMMSE receiver; however, the main drawback is that the computation of the auto-correlation \( R \) is very expensive. One can use the eigen-decomposition instead of inverting the auto-correlation matrix \( R \) as follows:

\[
b_{LMMSE}^W = S_i^H H_i (V_i D_i^{-1} V_i^H) \hat{r}
\]  

(12)

Where \( V_i \) is the estimated Eigen-vectors of the auto-correlation matrix \( R \), and \( D_i \) is the corresponding eigenvalue of the auto-correlation matrix \( R \). Additionally, one can use adaptive algorithms to estimate the LMMSE user’s symbols as in [32].

### IV. THE PROPOSED DETECTION SCHEMES BASED ON STATE SPACE FRAMEWORK

In this section, a new blind detection strategy is proposed, based on the state space structures. We propose the three blind multiuser detectors based on a feed-forward structure, a feedback structure I, and a feedback structure II, as shown in figures 3, 4 and 5, respectively.

Here, one needs to first recall the received signal model (3)

\[
r_n = H_0 b_n + H_1 b_{n-1} + n_n
\]

The aim of this paper is to detect the \( b \) symbol vector from the received data \( r \) under the following assumptions:

- AS1) the \( G \times K \) matrices \( H_0, H_1 \) are of full column rank.
- AS2) the symbol signals, \( b \), are white, independent and identically distributed (i.i.d).
- AS3) the Additive Noise vector is white and independent of source signals.
- AS4) the power of the transmitted symbol signals, are normalized to be unitary.
- AS5) the maximum lag in the entire multipath channels (\( \max(t_k) \)) is smaller than the spreading gain of the CDMA G.
- AS6) the CDMA system is not over-saturated, which means the number of users (\( K \)) is less than the the number of the spreading gain (\( G \)).
- AS7) the channel is assumed to be a slowly fading wide sense stationary.

Each method involves two steps; first, a preprocessing stage; second, the rotation stage based on the state space structures. In the next subsection, we will explain the preprocessing stage (whitening processes), and then we will derive the three methods based on each state space structure in individual subsections.
A. Step 1: Preprocessing (Data Whitening)

In the preprocessing step, the symbol signals are detected up to a unitary matrix using the second order statistic (SOS). This step was used to reduce the noise and to eliminate redundancy in the data. Under the Assumptions AS1, AS2, AS3 and AS4, the GxG covariance matrix \( C \) of the noiseless transmitted signals can be expressed by

\[
C = E[rr^H] - \sigma^2 I_N \tag{13}
\]

Without loss of generality, we will consider a single “two-tap” model. Then we will generalize them using induction techniques. Therefore, substituting \( r \) in (13), under our assumptions AS1-AS7, one can express the covariance matrix \( C \) as follows:

\[
C = H_0E[bb^H]H_0^H + H_1E[bb^H]H_1^H = H_0H_0^H + H_1H_1^H \tag{14}
\]

Under AS1, the \( H_0H_0^H \) and \( H_1H_1^H \) can be decomposed, respectively as

\[
C_0 = V_0\Lambda_0V_0^H \tag{15}
\]

\[
C_1 = V_1\Lambda_1V_1^H \tag{16}
\]

where \( V_0 \) and \( V_1 \) are an KxK matrix satisfying

\[
V_0V_0^H = V_0^HV_0 = I_K \tag{17}
\]

\[
V_1V_1^H = V_1^HV_1 = I_K \tag{18}
\]

and \( \Lambda_0 \) and \( \Lambda_1 \) are a KxK diagonal matrix containing significant eigenvalue entries. So, from (14), the GxG \( H_0 \) and \( H_1 \) matrices will be represented respectively as

\[
H_0 = V_0\Lambda_0^{-1/2}U_0^H \tag{19}
\]

\[
H_1 = V_1\Lambda_1^{-1/2}U_1^H \tag{20}
\]

where \( U_0 \) is a KxK full rank unitary matrix and \( U_0U_0^T = I_K \) and \( U_1 \) is a KxK full rank unitary matrix and \( U_1U_1^T = I_K \).

However, the whitening step obtained matrix \( V_0 \) and \( V_1 \) so that the KxK whitened data vector \( r_n^w \) has a covariance of the identity matrix, \( C = I_K \), which can be obtained as follows:

\[
r_n^w = \Lambda_0^{-1/2}V_0^HR_n + \Lambda_1^{-1/2}V_1^HR_n \tag{21}
\]

Therefore,

\[
r_n^w = U_0^Hb_n + U_1^Hb_{n-1} + \left( \Lambda_0^{-1/2}V_0^H + \Lambda_1^{-1/2}V_1^H \right) n_n \tag{22}
\]

The transmitted symbols can be recovered based on the state space structures. However, after the preprocessing step, the detection of the symbol signal \( \hat{b}_n \) reduces to determining the KxK unitary matrices \( U_k \) (rotation matrices). Next, the derivations for the three proposed algorithms, based on feed forward structure, feedback structure I and feedback structure II, respectively, are presented.

B. Step 2a: Determining the rotation matrix (unitary matrix) \( U \) based on the feedforward structure.

The output from the feedforward structure in Fig. 3 is given by

\[
y_n = U_0r_n^w + \sum_{k=1}^{K} U_k r_{n-k} \tag{23}
\]
By induction, the update law for the $k$th lag element is

$$u_{k+} = u_k - \mu r_n^w g(y_n)$$  

(28)

By induction, the update law for the $k$th lag element $u_k$ is

$$u_{k+} = u_k - \mu r_{n-k}^{-1} g(y_n)$$  

(29)

C. Step 2b: Determining the rotation matrix (unitary matrix) $U$ based on the feedback structure $I$.

The output of the feedback structure $I$ is given by

$$y_n = U_0^{-1} \left( r_n^w + \sum_{k=1}^{K} u_k y_{n-k} \right)$$  

(30)

Consider two tapes of the Feedback Configuration I model

$$y_n = U_0^{-1} \left( r_n^w + U_1 y_{n-1} \right)$$  

(31)

However, one can re-write the previous convolutive filter in the following augmented form

$$\begin{bmatrix} r_n^w \\ y_{n-1} \end{bmatrix} = \begin{bmatrix} U_0 & U_1 \\ \hline 0 & I \end{bmatrix} \begin{bmatrix} y_n \\ y_{n-1} \end{bmatrix}$$  

(32)

Or

$$\begin{bmatrix} y_n \\ y_{n-1} \end{bmatrix} = \frac{1}{\det(U_0)} \begin{bmatrix} I & -U_1 \\ \hline 0 & U_0 \end{bmatrix} \begin{bmatrix} r_n^w \\ y_{n-1} \end{bmatrix}$$  

(33)

This can be defined as

$$\tilde{Y} = \begin{bmatrix} y_n \\ y_{n-1} \end{bmatrix}$$

$$\tilde{W} = \begin{bmatrix} I & -U_1 \\ \hline 0 & U_0 \end{bmatrix}$$

$$\tilde{R} = \begin{bmatrix} r_n^w \\ y_{n-1} \end{bmatrix}$$

So, the previous augmented expression becomes

$$\tilde{Y} = \tilde{U}^T \tilde{R}$$

(34)

Based on the natural gradient method, the update law for the weight column of de-mixing matrix $\tilde{U}$, we have

$$u^+ = u - \mu E\left( g(u^T R) \right)$$

(35)

Where $u$ is the column vector of $\tilde{U}$, $\mu$ is the step size and $g$ is the score function. However,

$$u^0 = \begin{bmatrix} p^0 \\ -U_1^0 \end{bmatrix}$$  

(36)

The update law is

$$u_1^+ = v_1 - \mu g(r_n^w - u_1 y_{n-1})$$  

(37)

And

$$u^1 = \begin{bmatrix} 0^1 \\ U_0^1 \end{bmatrix}$$  

(38)

Then

$$u_0^+ = \begin{bmatrix} 0 \\ u_0 \end{bmatrix} - \mu g(y_{n-1})$$  

(39)

The update laws for the individual columns are

$$u_0^+ = u_0 - \mu y_{n-1} g(y_{n-1})$$  

(40)

And

$$u_1^+ = u_1 - \mu y_{n-1} g(r_n^w - u_1 y_{n-1})$$  

(41)

By induction, the update law for the $k$th lag element $u_k$ is

$$u_{k+} = u_k - \mu y_{n-k} g(r_n^w - u_k y_{n-k})$$  

(42)

D. Step 2c: Determining the rotation matrix (unitary matrix) $U$ based on the feedback structure $II$.

The output of the feedback structure $II$ is given by:

$$y_n = U_0 r_n^w + \sum_{k=1}^{K} U_k y_{n-k}$$  

(43)

Again, consider two tapes of the Feedback structure $II$ model

$$y_n = U_0 r_n^w + U_1 y_{n-1}$$  

(44)

However, one can re-write the previous convolutive filter in the following augmented form

$$\begin{bmatrix} y_n \\ y_{n-1} \end{bmatrix} = \begin{bmatrix} U_0 & -U_1 \\ \hline 0 & I \end{bmatrix} \begin{bmatrix} r_n^w \\ y_{n-1} \end{bmatrix}$$  

(45)

This can be defined as

$$\tilde{Y} = \begin{bmatrix} y_n \\ y_{n-1} \end{bmatrix}$$

Fig. 4. Feedback Demixing Structure I

u_0^+ = u_0 - \mu r_n^w g(y_n)$$  

(27)

Fig. 5. Feedback Demixing Structure II
\[ \mathbf{W} = \begin{bmatrix} U_0 & 0 \\ -U_1 & I \end{bmatrix} \]

\[ \mathbf{R} = \begin{bmatrix} r^W_n \\ y_{n-1} \end{bmatrix} \]

So, the previous expression becomes

\[ \tilde{Y} = \tilde{U}^T \tilde{R} \quad (46) \]

Based on the natural gradient method, the update laws for the weight column of de-mixing matrix \( \tilde{U} \), we have

\[ u^+ = u - \mu E \left( R \left( g(u^T \tilde{R}) \right) \right) \quad (47) \]

Where \( u \) is the column vector of \( \tilde{U} \), \( \mu \) is the step size and \( g \) is the score function. However,

\[ u = \begin{bmatrix} u_0 \\ u_1 \end{bmatrix} \]

Then

\[ \begin{bmatrix} u_0^+ \\ u_1^+ \end{bmatrix} = \begin{bmatrix} u_0 \\ u_1 \end{bmatrix} - \mu \begin{bmatrix} r^W_n \\ y_{n-1} \end{bmatrix} g(y_n) \quad (49) \]

\[ \text{Algorithm 1: RAKE based FastICA method} \]

Input: \((M \times T)\) matrix of realization \( r \), Initial demixing matrix \( \mathbf{W} = \mathbf{I}_G \), number of iterations \( I_{fr} \), Step Size \( \gamma \)

Perform Pre-Whitening

\[ r = V^* r = A^c((-1) / 2) E^T r \]

For loop: for each \( i = 1 \ldots N \)

\[ R = WH^H r(:, i) \]

\[ W = E((g(WR))^T) - E(g^2(WR))W \]

\[ W = W / \text{norm}(W) \]

\[ b^D_{\text{LICA}}(:, i) = S_l^W WH^H r \]

Output: the estimated Symbols \( b^D_{\text{LICA}} \)

\[ \text{Algorithm 2: RAKE based RICA method} \]

Input: \((M \times T)\) matrix of realization \( r \), Initial demixing matrix \( \mathbf{W} = \mathbf{I}_G \), number of iterations \( I_{fr} \), \( \mathbf{H} \) is the estimated channel matrix, here \( g \) is the gradient of the Kurtosis contrast \( K(.) \)

Perform Pre-Whitening

\[ r = V^* r = A^c((-1) / 2) E^T r \]

For loop: for each \( i = 1 \ldots N \)

\[ R = WH^H r(:, i) \]

\[ \Delta W = (I_G - R R^H) W \]

\[ W = W + \gamma \Delta W \]

\[ W = W / \text{norm}(W) \]

\[ b^D_{\text{RICA}}(:, i) = S_l^W WH^H r \]

Output: the estimated Symbols \( b^D_{\text{RICA}} \)

By induction, the update law for the \( k \)th lag element \( u_k \) is

\[ u_k^+ = u_k - \mu y_{n-k} g(y_n) \quad (52) \]

E. The proposed adaptive detectors

In this section, we develop three adaptive detectors based the Independent Component Analysis (ICA), Robust ICA and Principle Component Analysis (PCA). Owning the RAKE receiver structure in (10), one can express the adaptive weight RAKE for DS-CDMA system mathematically as follows:

\[ b^D_{\text{RAKE}} = S_l^W WH^H r \quad (53) \]

Where \( H \) is the estimated channel matrix, \( b^D_{\text{RAKE}} \) is the estimated \( i \)th user’s symbol, and \( W \) is a \( G \times G \) weighting matrix. However, we present Algorithms 1 2 and 3 to estimate the matrix \( W \) adaptively based on the FastICA, Robust ICA and PCA algorithms, respectively.

\[ \text{Algorithm 3: RAKE based PCA method} \]

Input: \((M \times T)\) matrix of realization \( r \), Initial demixing matrix \( \mathbf{W} = \mathbf{I}_G \), number of iterations \( I_{fr} \), Step Size \( \gamma \) i.e. \( \gamma = 0.3 \), \( \mathbf{H} \) is the estimated channel matrix.

Perform Pre-Whitening

\[ r = V^* r = A^c((-1) / 2) E^T r \]

For loop: for each \( i = 1 \ldots N \)

\[ R = WH^H r(:, i) \]

\[ \Delta W = (I_G - R R^H) W \]

\[ W = W + \gamma \Delta W \]

\[ W = W / \text{norm}(W) \]

\[ b^D_{\text{PCA}}(:, i) = S_l^W WH^H r \]

Output: the estimated Symbols \( b^D_{\text{PCA}} \)

V. SIMULATION RESULTS

In this section, a series of simulations are carried out in order to verify the proposed algorithms in the multipath downlink DS-CDMA system in the presence of AWGN. We assume a constant spreading gain, which is \( N_G = 63 \) for Gold Codes and \( N_G = 64 \) for Orthogonal Variable Spreading Factor (OVSF) codes. The received CDMA signal is taken in five multipath channels \( L = 5 \) with delays of \( \{0, 1, 2, 3, 4\} \) chips, respectively. Also, we use the complex attenuation coefficients to represent the multipath channels, which are \( h_0 = 0.3684 + 0.5364i \), \( h_1 = 0.1982 + 0.0187i \), \( h_2 = 0.0237 + 0.5683i \), \( h_3 = 0.1112 + 0.0835i \), and \( h_4 = 0.2203 + 0.2756i \), respectively. We use the following model function for sub-Gaussian sources in which the source signals have a negative kurtosis sign.

\[ g_{\text{sub}}(b) = b - (\tanh(\text{Re}(b)) + j\tanh(\text{Im}(b))) \quad (54) \]

Monte Carlo Simulation was run to verify the validity of the algorithm simulations. Also, we use the signal-to-noise ratio (SNR) as a figure of merit which merely represents the ratio of the energy per bit and the power spectral density.
(PSD) of the noise. Moreover, all the user symbols are assumed to be transmitted with the same power. Fig. 6 (a) and (b) show the simulation results of SNR vs. BER for the proposed detectors regarding to the conventional ones for number of users $K=30$ and $K=50$, respectively. The other parameters were set as: Number of symbols $M=1000$, Number of paths $L=5$, with various values of SNR -10 dB to 30 dB.

In Fig. 6, the proposed algorithms improve the performance of the CDMA system; blind multiuser detection based on the second feedback structure has given the lowest BER when compared to the others, and outperforms the other detectors. We also observe that the proposed algorithms work even in cases which cause problems for the LMMSE receiver, such as in a high SNR ratio, especially when the sample set $T$ is fairly small. Moreover, the performance of the blind multiuser detection degrades as the number of users increases as shown in Fig. 6 (b).

In the WCDMA System, we assume that the channel coefficients are $h_0 = 0.3684 + 0.5364i$, $h_1 = 0.1982 + 0.0187i$, $h_2 = 0.0237 + 0.5683$, $h_3 = 0.1112 + 0.0835i$, and $h_4 = 0.2203 + 0.2756i$, respectively; the bandwidth of a channel is 1.25 mega chips per second (MCPs); and all user-specific codes use two types of spreading codes, namely, Gold codes with spreading gain $G=63$ and OVSF (or Walsh-Hadamard) codes with spreading gain $G=64$.

In Fig. 8 and 9, we demonstrate the performance of the various methods in terms of BER for the WCDMA downlink scenario. We observe that the LMMSE is slightly better than some presented detectors under the good SNR conditions. But the proposed algorithm based on the second feedback structure...
outperforms all detectors at all SNR and has again given the lowest BER when compared to the others.

![Graph](image_url)

It is also worthwhile to compare the presented algorithms with a large data sample set. Thus, Fig. 10 and Fig. 11 represent the performance of the various detectors with fairly long sample M=30 000 in the DS-CDMA and WCDMA systems, respectively. It’s plausible to assume that the LMMSE detector becomes better than other detectors under good SNR conditions. However, the proposed algorithm based on the feed backward second configuration has exceeded the LMMSE detector at all SNRs less than 22dB.

Finally, we studied the effect of the size of the sample set and the number of users on the performance of the proposed method in Fig. 12 and 13, respectively. Thus, Fig. 13 shows the simulation results of BER vs. SNR with 30 users (K=30) for various data samples (M). Although the proposed algorithm seems robust for sample sets and performs well, it is obvious that the proposed algorithm also improves more consistently in the performance as M increases and mitigates the MIA. In Fig. 13, the simulation results show the BER vs. SNR with various K users at 500 symbols for each user for blind multiuser detection based on the second feedback structure detector. It shows that the proposed detector performs less as K increases. Overall, the proposed algorithm outperforms other algorithms in most cases and performs better to solve the symbol estimation problem in the DS/WCDMA downlink system, especially when the size of the sample set is relatively small.

VI. CONCLUSION

This paper carried out both simulation and theoretical demonstrations of the blind multiuser detector based on the space state structures in the CDMA system. Also, we develop the three blind multiuser detectors based on the three algorithms ICA, RICA and PCA. The results appear to show that the proposed algorithms perform well in the symbol estimation problem in DS/CDMA systems and outperform the other conventional detectors and the Adaptive MMSE. Our results also show that Multiple Access Interference (MAI) can be mitigated by the proposed algorithms, thus improving the performance of blind multiuser detection. Although the proposed method improves as the size of the sample set increases, the results show the proposed detector performs well even though the sample sets are small, unlike the LMMSE detector. Moreover, unlike the complexity of the LMMSE detector, the complexity of the proposed methods, being constant, didn’t increase exponentially. Finally, the proposed algorithms, unlike the adaptive LMMSE detector, have no restriction regarding the spreading codes since they do not require the spreading codes of the interfering users. Therefore, it is a more suitable choice in the downlink case and it does work in the uplink case as well.

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Fig. 9: Average BER as a function of SNR for WCDMA downlink. Using OVSF codes \( G = 64 \). (a) Using 30 users (b) Using 50 users

Fig. 10: Average BER as a function of SNR for DS-CDMA downlink. For 30 users (a) Using Gold codes \( G = 63 \). (b) Using OVSF codes \( G = 64 \).
Fig. 12: Average BER as a function of SNR for various number of users $K$.

Fig. 13: Average BER as a function of SNR for various sample sets $M$.

(a) Number of users $K = 30$, Using Gold codes $G = 63$.
(b) Number of users $K = 30$, Using OVSF codes $G = 64$.

Fig. 11: Average BER as a function of SNR for WCDMA downlink. For 30 users (a) Using Gold codes $G=63$. (b) Using OVSF codes $G=64$. 