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An Implementation of Nonlinear Multiuser Detection in Rayleigh Fading Channel

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A blind nonlinear interference cancellation receiver for code-division multiple-access- (CDMA-) based communication systems operating over Rayleigh flat-fading channels is proposed. The receiver which assumes knowledge of the signature waveforms of all the users is implemented in an asynchronous CDMA environment. Unlike the conventional MMSE receiver, the proposed blind ICA multiuser detector is shown to be robust without training sequences and with only knowledge of the signature waveforms. It has achieved nearly the same performance of the conventional training-based MMSE receiver. Several comparisons and experiments are performed based on examining BER performance in AWGN and Rayleigh fading in order to verify the validity of the proposed blind ICA multiuser detector.

1. INTRODUCTION

In mobile communication systems, multiuser detection is also known under the names of cochannel interference suppression, multiuser demodulation, or interference cancellation, and requires rather complicated high-precision power control. The design of multiuser detectors has been motivated by the channel environment encountered in many CDMA applications, for channels with fading, multipath, or noncoherent modulation have been considered [1, 2]. In particular, recent focus has been on the blind (or non-data-aided) multiuser detectors such as SIC [3], PIC [4], and DFD [5], these *require no training data sequence, but only knowledge of the desired user signature sequence and its timing* [6]. The main motivation of employing a blind multiuser detector in CDMA is to recover the original sequence from the received signal that is corrupted by noise and MAI, *without* the help of training sequences and a priori knowledge of the channel. Prior work by Ristaniemi and Joutsensalo [7] leads to the proposal of two types of receivers, RAKE-ICA and MMSE-ICA, in a Rayleigh fading channel using the modified FastICA algorithm [8]. However, the estimation of eigenvectors and eigenvalues becomes an additional burden for the proposed RAKE-ICA. Also, the MMSE-ICA which required training sequences causes an increase in computational load. An adaptive multiuser detector, which converges to the MMSE detector without requiring training sequences, is proposed in [1]. This detector is designed with incomplete knowledge of the received signature waveform of the desired user. In [9], a blind adaptive multiuser detector based on Kalman filtering for both stationary and slowly time-varying environments has been proposed, and it is shown that the steady-state excess output energy of the Kalman filtering algorithm is strictly zero for a statistically stationary environment. A overview of adaptive tentative-decision-based detectors is given by Verdu in [2]. It was mentioned that a linear MMSE detector has the features of a decorrelating detector, except that it requires knowledge of the received amplitudes. On the other hand, the tentative-decision-based multiuser detector is the simplest idea for successive cancellation, but its disadvantage is that it requires extremely accurate estimation of the received amplitudes [2, 10]. The work of Verdu has also provided an exceptionally important reference and guide for the implementation of the subsequent work.

The objective of this paper is to introduce a blind multiuser detector that adaptively recovers signals from multiple users. The proposed blind multiuser detector is capable of replacing the conventional MMSE detector which requires training sequences and the original transmitted signals. This is achieved based on independent component analysis (ICA) [11, 12] used at the outputs of a bank of matched filters.

The rest of this paper is organized as follows. Section 2 describes the CDMA communication model and decision statistics. This is followed by an introduction of the proposed ICA algorithm in Section 3. Performance analysis and simulation results are presented in Section 4 to demonstrate the performance of the new proposed detector and make a comparison with the other conventional detectors. Finally, discussions and conclusions are given in Section 5 and Section 6.

2. BACKGROUND

2.1. Multiuser communication model

Let us first derive the decision statistic for the proposed blind nonlinear multiuser receiver structure. The main principle of the receiver is that for a given decoding order, the received signal is first passed through a correlator. The soft output of the correlator is then used to detect the first signal. We present expressions for the probability of the bit error for an AWGN channel with constant (although not necessarily equal) received user energies. These analytical results are then compared with simulation results.

2.2. System model

Consider a time-invariant flat-fading asynchronous uplink CDMA channel. The received baseband signal, $r(t)$, in an antipodal K-user BPSK modulated system is given by

$$r(t) = \sum_{i=-J}^{J} \sum_{k=1}^{K} g_k A_k b_k(i) s_k(t - iT_s - \tau_k) + \sigma n(t), \quad (1)$$

where $2J + 1$ denotes the number of data symbols per user per frame.

(i) g_k is the channel gain for the kth user.
(ii) A_k is the transmitted amplitude of the kth user.
(iii) $b_k(i)$ is the ith (independent binary input) data symbol of the kth user, $b_k \in \{-1, +1\}$.
(iv) The kth signature waveform s_k is determined by the random pseudonoise (PN) spreading sequence c_k and pulse-shape waveform $p(t)$, given by

$$\begin{gathered} s_k(t) = \sum_{i=0}^{N_{PG}-1} c_k(i) p(t - iT_c) \quad \text{for } 0 \le t \le T_s, \\ s_k(t) = s_k(t - mT_s) \quad \text{for } t \text{ otherwise}, \\ \text{where } m = \text{integer}, \end{gathered} \quad (2)$$

where $s_k(t)$ is assumed to have unit energy over the symbol interval: $T_s = N_{PG} T_c$ symbol interval; T_c chip interval; N_{PG} processing gain.
In this work, s_k is generated by Gold code sequences. These signature sequences are independent of the data symbols and have a chip rate much higher than the symbol rate.
(v) The kth signature waveform s_k is assumed to have unit energy ($\int_0^T |s_k|^2 dt = 1$). $\tau_k \in [0, T_s)$ is the kth user's relative time offset, where T_s is the symbol period.
(vi) The additive white Gaussian noise $n(t)$ has unit power spectral density.
(vii) σ^2 is the variance of the additive noise.

We assume completely asynchronous transmission. In this context, when there are timing errors, each user's code experiences a random delay during the transmission and the received signal is no longer aligned with the locally generated codes [13]. We consider the received signal $r(t)$ over only one symbol period that is asynchronous to the desired user.

2.3. Correlator and crosscorrelation matrix

An important multiuser detection issue [14] is the representation via sampling of $r(t)$ as a vector in a continuous finite-dimensional linear space:

$$r_i(t) = \sum_{k=1}^{K} g_k A_k b_k(i) s_k(t - iT_s - \tau_k) + \sigma n(t). \quad (3)$$

The representation of $r(t)$ could be easier if no narrowband interference were present and the delays were known a priori. However, such an assumption is not realistic and would affect the implementation of adaptive receivers. Therefore, it is customary to apply the $r(t)$ to chip-matched filtering.

At the receiver, the matched-filter bank is designated at the first stage in the baseband signal detection. For each user, a correlation is performed between the received signal $r(t)$ and the user spreading waveform. The sampled output of the matched filter for the ith bit of the kth user is

$$x_k(i) = \frac{1}{T_s} \int_0^{T_s} r_i(t) s_k(t - iT_s - \tau_k + \Delta\tau_k) dt, \quad (4)$$

where $\Delta\tau_k$ denotes timing or synchronization error, which is minimized through the use of, for example, correlation-based time-delay estimation. The (k, j)th element of the $K \times K$ normalized signal crosscorrelation matrices β whose entries $\rho = \beta_{kj}$ are given by

$$\rho(i) = \frac{1}{T_s} \int_0^{T_s} s_k(t - iT_s - \tau_k) s_j(t) dt. \quad (5)$$

Since the modulating signals are zero outside $[0, T_s]$, we define

$$\begin{gathered} \beta(i) = 0 \quad \forall |i| > 1, \\ \beta(-i) = \beta^T(i), \end{gathered} \quad (6)$$

where the NK matrix $\mathfrak{R}$ is

$$\mathfrak{R} = \begin{pmatrix} \beta(0) & \beta(-1) & 0 & \cdots & 0 \\ \beta(1) & \beta(0) & \beta(-1) & \cdots & \vdots \\ 0 & \beta(1) & \beta(0) & \cdots & 0 \\ \vdots & \vdots & \vdots & \cdots & \beta(-1) \\ 0 & 0 & 0 & \cdots & \beta(0) \end{pmatrix}. \quad (7)$$

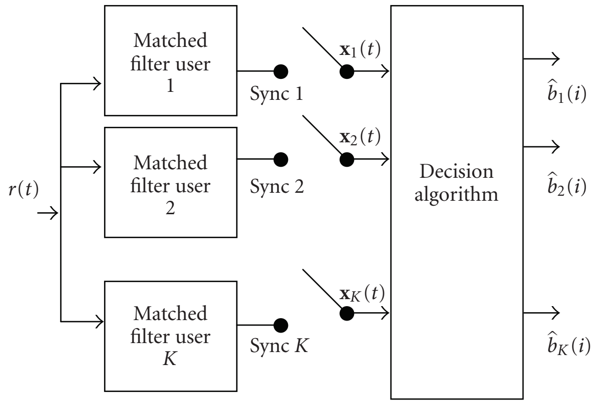

FIGURE 1: K-user detectors for multiple-access Gaussian channel.

Generally, there are no cross-links among the filters. Each branch of the matched-filter bank consists of the correlation operation of the received signal with one particular user's signature sequence as illustrated in Figure 1.

2.4. Channel

In multiple-access channels, not only do the received amplitudes vary with time, but so too do the received signature waveforms, due to channel distortion. In this work, we consider Rayleigh distributed signal amplitudes. The Rayleigh distribution model is particularly suitable for non-line-of-sight (NLOS) communication links, to describe the statistical time-varying natures of the received envelope of a flat-fading signal. This arises when the process is zero mean, its phase is uniformly distributed on $[0, 2\pi)$, and g_k has its pdf in the form of

$$f(g_k) = \frac{g_k}{\sigma^2} \exp\left(-\frac{g_k}{2\sigma^2}\right), \quad 0 \le g_k < \infty, \tag{8}$$

where σ is the *rms* value of the received voltage signal before the envelope detection, σ^2 is the time-average power of the received signal before the envelope detection, and g_k is the path amplitude.

Referring to (1) and (3) (the first-order statistics of the received amplitude probability density function of $|g_k(i)|$), it can be written as the product of a deterministic component and a random component which is Rayleigh distributed, g_k:

$$|g_k(i)| = g_k \mathbf{R}(i), \tag{9}$$

where $\mathbf{R}(i)$ is a stationary ergodic Rayleigh-distributed random process whose first-order probability density function is shown in (8).

2.5. Source independence

In the CDMA downlink receiver, both code timing and channel estimation are often prerequisites. Detection of the desired user's symbols in CDMA system is far more complicated than in the previous simpler TDMA and FDMA systems. Our main goal is therefore to estimate and recover the original transmitted symbols. Several techniques are currently available to estimate the desired user's symbols. In general, the matched filter (correlator) is the simplest estimator, but it performs well only if different users' chip sequences are orthogonal and the users' received signals have equal powers [15].

To that case, we propose to apply ICA to design a new blind receiver. The main reason for using ICA in the CDMA receiver is due to its resistance to strong interference [9] and because each user path and user transmitted symbol sequence are approximately independent of one another.

3. THE PROPOSED ICA ALGORITHM

The proposed ICA learning algorithm (see Figure 2) requires K matched filters to provide multiple mixtures of the K transmitted user signals. We assume the mixtures are linear, so that the relationship between the vector of K received signals $\mathbf{X}(i) = [x_1(i), x_2(i), \dots, x_K(i)]^T$ and the vector of K transmitted bit sequences can be expressed as

$$\mathbf{X}(i) = \mathbf{G}\mathbf{B}(i) + \sigma\mathbf{N}(i), \tag{10}$$

where $\mathbf{B}(i) = [b_1(i), b_2(i), \dots, b_k(i)]^T$, $\mathbf{G}$ is the corresponding $K \times K$ linear mixing matrix, and $\mathbf{N}(i) = [n_1(i), \dots, n_K(i)]^T$ is the corresponding additive white Gaussian noise vector.

The proposed algorithm consists of three stages: (i) principle component analysis (PCA), (ii) independent component analysis (ICA), and (iii) denoising. The ICA learning algorithm is generalized from Amari's natural gradient algorithm [16] mainly in terms of applying cost functions to multivariate data. The minimization of the cost function is performed according to stochastic gradient descent and will be discussed later. Wavelet denoising [17] may also be employed to reduce the effects of the Gaussian noise.

3.1. Principle component analysis

PCA-based whitening and sphering (the mean becomes zero and the standard deviation one) of the received data $\mathbf{X}(i)$ is a common preprocessing technique in ICA. It is usually performed before the application of ICA as a means to reduce the effect of first- and second-order statistics, and to speed up the convergence process. It helps to reduce the number of unknowns in the mixing matrix, so that the remaining mixture can be modelled by a simpler orthogonal matrix [9]. This method has the additional advantage of decorrelating the sensor signals before separation. It makes the subsequent separation task easier, so that the separating matrix is constrained to be orthogonal. There is no explicit assumption on probability densities [18], as long as the first- and second-order statistics are known or can be estimated from the mixture. The origin of PCA relies on the following problem. For the multidimensional vector $\mathbf{X}(i)$, find a linear transform $\mathbf{F}$ such that the obtained components are uncorrelated:

$$\mathbf{u}(i) = \mathbf{F}[\mathbf{X}(i) - E\{\mathbf{X}(i)\}]. \tag{11}$$

That is,

$$\S_u = E\{\mathbf{u}\mathbf{u}^H\} \tag{12}$$

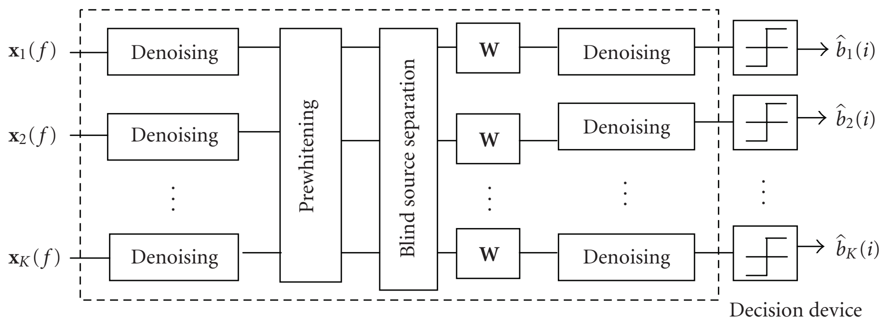

Figure 2: The proposed blind receiver consisting of PCA, ICA, and denoising stages.

is diagonal, where $\mathbf{u}(i) = [u_1(i), u_2(i), \ldots, u_K(i)]^T$ and $(\cdot)^H$ denotes the Hermitian transpose operator. The vector of the expected values $E\{\mathbf{u}\}$ and the covariance matrix $\S_u$ can be expressed in terms of the vector of expected values and covariance matrix for $\mathbf{X}(i)$:

$$\begin{aligned} E\{\mathbf{u}\} &= \mathbf{F}[E\{\mathbf{X} - E\{\mathbf{X}\}\}] = 0, \\ \S_u &= E\Big\{(\mathbf{FX} - \mathbf{F}E\{\mathbf{X}\})(\mathbf{FX} - \mathbf{F}E\{\mathbf{X}\})^H\Big\} \\ &= E\Big\{\mathbf{F}(\mathbf{X} - E\{\mathbf{X}\})(\mathbf{X} - E\{\mathbf{X}\})^H\mathbf{F}^H\Big\} \\ &= \mathbf{F}E\Big\{(\mathbf{X} - E\{\mathbf{X}\})(\mathbf{X} - E\{\mathbf{X}\})^H\Big\}\mathbf{F}^H \\ &= \mathbf{F}\S_x\mathbf{F}^H. \end{aligned} \tag{13}$$

Let Ψ_x be the matrix formed from the normalized eigenvectors for the covariance matrix $\S_x$, then

$$\mathbf{D}_x = \Psi_x^H \S_x \Psi_x \tag{14}$$

is the corresponding diagonal eigenvalue matrix. The PCA whitened signals are given by

$$\mathbf{u}(i) = \mathbf{D}_x^{1/2}\Psi_x^H(\mathbf{X}(i) - E\{\mathbf{X}(i)\}), \tag{15}$$

where $\mathbf{D}_x^{1/2}\Psi_x^H = \mathbf{F}$ is the PCA whitening linear transform.

In the following, we proceed to derive an algorithm for estimating the linear unmixing $K \times K$ matrix $\mathbf{W}$ such that the elements of the generated output vector $\mathbf{y}(i) = \mathbf{Wu}(i)$, $\mathbf{y}(i) = [y_1(i), y_2(i), \ldots, y_K(i)]^T$, have minimum mutual information. The goal is to determine the gradient of the mutual information with respect to the elements of $\mathbf{W}$. Essentially, $\mathbf{W}$ is an estimate of $\mathbf{G}^{-1}$, where $\mathbf{G}$ is unknown mixing matrix. Once such a gradient is computed, update the elements of $\mathbf{W}$ in the gradient-based optimization algorithm [16]:

$$\mathbf{W} = \mathbf{W} + \Delta\mathbf{W} = \mathbf{W} - \alpha\frac{\partial \mathfrak{I}(y_1, \ldots, y_K)}{\partial \mathbf{W}}, \tag{16}$$

where α denotes the learning rate.

In order to compute the gradient algorithm, we expand the mutual information between output signals as follows:

$$\begin{aligned} \mathfrak{I}(y_1, \ldots, y_K) &= E\{\log p(\mathbf{u})\} \\ &\quad - \log(\det \mathbf{W}) - \sum_{i=1}^{K} E\{\log p(y_i)\}. \end{aligned} \tag{17}$$

When the mutual information $\mathfrak{I}(\mathbf{y})$ is equal to zero, the output variables are statistically independent. The gradient of $\mathfrak{I}(y_1, \ldots, y_K)$ with respect to $\mathbf{W}$ can be expressed as

$$\begin{aligned} \frac{\partial \mathfrak{I}(y_1, \ldots, y_K)}{\partial \mathbf{W}} &= \frac{\partial E\{\log(p(\mathbf{u}))\}}{\partial \mathbf{W}} - \frac{\partial\{\log(\det \mathbf{W})\}}{\partial \mathbf{W}} \\ &\quad - \frac{\partial \sum_{i=1}^{K} E\{\log(p(y_i))\}}{\partial \mathbf{W}} \\ &= -\frac{\partial\{\log(\det \mathbf{W})\}}{\partial \mathbf{W}} - \sum_{i=1}^{K} \frac{\partial E\{\log(p(y_i))\}}{\partial \mathbf{W}} \end{aligned} \tag{18}$$

since the first term $E\{\log p(\mathbf{u})\}$ does not involve $\mathbf{W}$. We will analyze the two remaining terms separately. For the first term, we have

$$\begin{aligned} \frac{\partial\{\log(\det \mathbf{W})\}}{\partial \mathbf{W}} &= \frac{1}{\det \mathbf{W}} \frac{\partial \det \mathbf{W}}{\partial \mathbf{W}} \\ &= \frac{1}{\det \mathbf{W}}(\operatorname{adj}(\mathbf{W}))^H = (\mathbf{W}^{-1})^H. \end{aligned} \tag{19}$$

A family of nonlinear functions $g_i(\cdot)$ is adapted in ICA, such that they approximate the probability density function of every y_i.

Accordingly,

$$\begin{aligned} \sum_{k=1}^{K} &\frac{\partial E\{\log(p(y_k))\}}{\partial \mathbf{W}} \\ &= \sum_{k=1}^{K} E\left\{\frac{1}{g_k(y_k)} \frac{\partial g_k(y_k)}{\partial(y_k)} \frac{\partial y_k}{\partial \mathbf{W}}\right\} \\ &= E\begin{pmatrix} \frac{1}{g_1(y_1)}\frac{\partial g_1(y_1)}{\partial(y_1)}u_1 & \cdots & \frac{1}{g_1(y_1)}\frac{\partial g_1(y_1)}{\partial(y_1)}u_K \\ \vdots & & \vdots \\ \frac{1}{g_K(y_K)}\frac{\partial g_K(y_K)}{\partial(y_K)}u_1 & \cdots & \frac{1}{g_K(y_K)}\frac{\partial g_K(y_K)}{\partial(y_K)}u_K \end{pmatrix} \\ &= E\left\{\frac{1}{\mathbf{g}(\mathbf{y})} \frac{\partial \mathbf{g}(\mathbf{y})}{\partial(\mathbf{y})} \mathbf{u}^H\right\}, \end{aligned} \tag{20}$$

where $\mathbf{g}(\mathbf{y}) = [g_1(y_1), \ldots, g_K(y_K)]$. Finally, we compute an approximation to the gradient of $\mathfrak{I}(y_1, \ldots, y_K)$ and the update step is multiplied with the $\mathbf{W}^H\mathbf{W}$:

$$\begin{aligned}\Delta\mathbf{W} &= -\frac{\partial\mathfrak{I}(\mathbf{y})}{\partial\mathbf{W}}\mathbf{W}^H\mathbf{W} \\ &= \left(\mathbf{W}^H\right)^{-1}\mathbf{W}^H\mathbf{W} + E\left\{\left(\frac{1}{\mathbf{g}(\mathbf{y})}\frac{\partial\mathbf{g}(\mathbf{y})}{\partial\mathbf{y}}\right)\mathbf{u}^H\mathbf{W}^H\right\}\mathbf{W} \\ &= \mathbf{W} + E\{h(\mathbf{y})\mathbf{y}^H\}\mathbf{W},\end{aligned} \tag{21}$$

where

$$h(\mathbf{y}) = \frac{1}{\mathbf{g}(\mathbf{y})}\frac{\partial\mathbf{g}(\mathbf{y})}{\partial\mathbf{y}}. \tag{22}$$

It can be proved that use of the natural gradient not only preserves the direction of the gradient but also speeds up the convergence process. The minimum mutual information algorithm for ICA will repeatedly perform an update of the matrix $\mathbf{W}$:

$$\mathbf{W} = \mathbf{W} + \alpha\Delta\mathbf{W}, \tag{23}$$

where α is a "small" update coefficient that controls the convergence speed.

A robust formulation of (23) requires that each $g_i(y_i)$ is a nonlinear function of any symmetric density. These nonlinear functions are essential for the accuracy of the algorithm. Ideally the nonlinear function $g_i(y_i)$ approximates the probability density function of y_i. It was suggested to model these functions by a weighted sum of parametric logistic functions [16, 19]. Some experimental evidence [11] has indicated that even with a single fixed nonlinearity, the minimum mutual information algorithm converges very close to the optimal ICA solution. The success with using only one function is due to the corresponding independent sources being transforms of the initial independent sources. It is, however, important to indicate that "not all functions are equal." Approaches involving prediction of the nature of the sources along with a switch between sub-Gaussian and super-Gaussian functions have been proposed [3, 5, 10]. Alternatively, we now apply a nonlinear function $\mathbf{g}(\mathbf{y})$ as in [16]:

$$g_i(y_i) = \tanh(y_i). \tag{24}$$

After initializing the weight matrix $\mathbf{W}_0$ as an identity matrix $\mathbf{I}$, and choosing α to be a sufficiently small constant, such as $\alpha = 0.0001$, the weights are iteratively updated according to the learning rule given by

$$\mathbf{W}_{p+1} = \mathbf{W}_p + \alpha\left(\mathbf{I} + h(\mathbf{y}_p)\mathbf{y}_p^H\right)\mathbf{W}_p, \tag{25}$$

where p is the iteration index, and the estimated output $\mathbf{y}_p(i) = \mathbf{W}_p\mathbf{u}(i)$.

The outline of the proposed algorithm is given by the following.

(1) Prewhiten the matched filtered received signals

$$\mathbf{u}(i) = \mathbf{D}_x^{-1/2}\Psi_x^H\left(\mathbf{X}(i) - E\{\mathbf{X}(i)\}\right). \tag{26}$$

(2) Select the initial separating matrix $\mathbf{W}_0$ and the learning rate α.
(3) Estimate the initial output, $\mathbf{y}_0(i) = \mathbf{W}_0\mathbf{u}(i)$.
(4) Update the separating matrix by

$$\mathbf{W}_{p+1} \longleftarrow \mathbf{W}_p + \alpha\left(\mathbf{I} + h(\mathbf{y}_p)\mathbf{y}_p^H\right)\mathbf{W}_p. \tag{27}$$

(5) Decorrelate and normalize $\mathbf{W}_{p+1}$.
(6) If $|(\mathbf{W}_{p+1})^H\mathbf{W}_p|$ is not close enough to 1, then $p = p+1$, and go back to step (4). Else, keep the matrix $\mathbf{W}_p$ where the output signals; $\mathbf{y}_p(i) = \mathbf{W}_p\mathbf{u}(i)$.
(7) Output detector, $\operatorname{sgn}(\mathbf{y}_p(i))$.

4. EXPERIMENTS AND RESULTS

Experiments were presented to compare the performance of the proposed blind ICA multiuser detector with the decorrelating detector, matched-filter bank, SIC [3], PIC [4], and DFD [5].

Example 1. The environment considered was the uplink of a simplified CDMA system over a slow Rayleigh fading channel. The receiver output SNR is used as the evaluation index. Also, the input SNR is defined as $\text{SNR}_i = \mathbf{P}/\sigma^2$, where we assume equal power MAI for convenience. The channel model adopted for simulations was an unknown Rayleigh flat-fading channel in which the fading gains were independent, identically distributed complex Gaussian random variables with zero mean and unit variance. The path delays τ_k were assumed uniform over $[0, 5T_c]$. The chosen learning rate was $\alpha = 0.000001$ and number of iterations, $p = 200$.

All CDMA signals were generated with BPSK data modulation and Gold codes of length $N_{GC} = 31$ and $N_{GC} = 127$ were used as the spreading codes. Unless otherwise stated, the following parameters were assumed: processing gain, $N_{PG} = 31$ and $N_{PG} = 127$, $\text{SNR}_i = 0\,dB$, doppler bandwidth, $f_D = 10\,\text{Hz}$, sampling frequency, $f_s = 2\,\text{kHz}$, and number of users, $K = 10$.

The bit error rate (BER) performance of the proposed blind ICA receiver in the slow Rayleigh fading channel is presented in Figures 3 and 4. The results show that when the processing gain $N_{PG} = 127$, the standard matched filter receiver was significantly outperformed by each of the other training (linear MMSE) and/or blind multiuser detectors and that each of these alternative detectors gave nearly equivalent performance.

Greater performance discrimination between the detectors was observed when the processing gain $N_{PG} = 31$. Again, each of the alternative detectors significantly outperformed the standard matched-filter receiver. However, in this case, at increasing SNR the proposed blind ICA receiver significantly outperformed the other blind multiuser detectors (successive interference cancellation detector (SIC), parallel interference

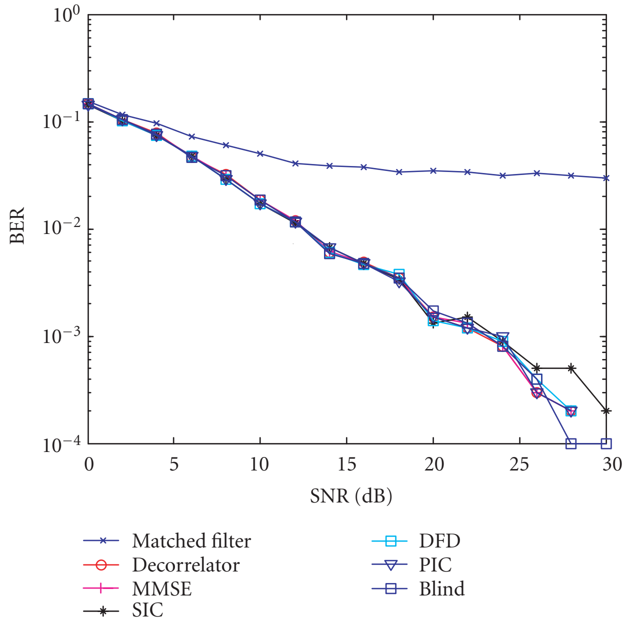

FIGURE 3: BER performance comparison between the proposed blind ICA multiuser receivers and the other conventional receivers in a slow-fading channel with the $f_D = 10\,\text{Hz}$, $T_s = 10^{-4}$, number of the users, $K = 10$, processing gain, $N_{PG} = 127$.

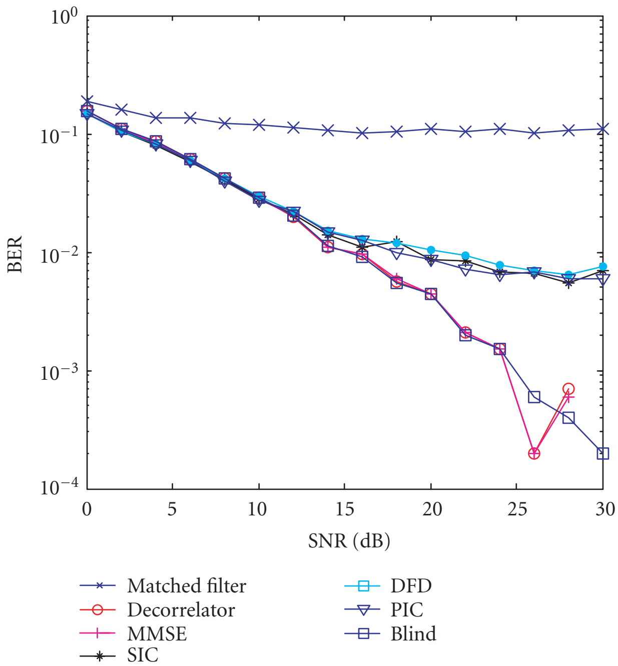

FIGURE 4: BER performance comparison between the proposed blind ICA multiuser receiver and the other receivers in a slow Rayleigh channel with the number of the users, $K = 10$, $f_D = 10\,\text{Hz}$, $T_s = 10^{-4}$, processing gain, $N_{PG} = 31$.

cancellation detector (PIC), and decision-feedback detector (DFD)). From Figure 3, the performance of the proposed

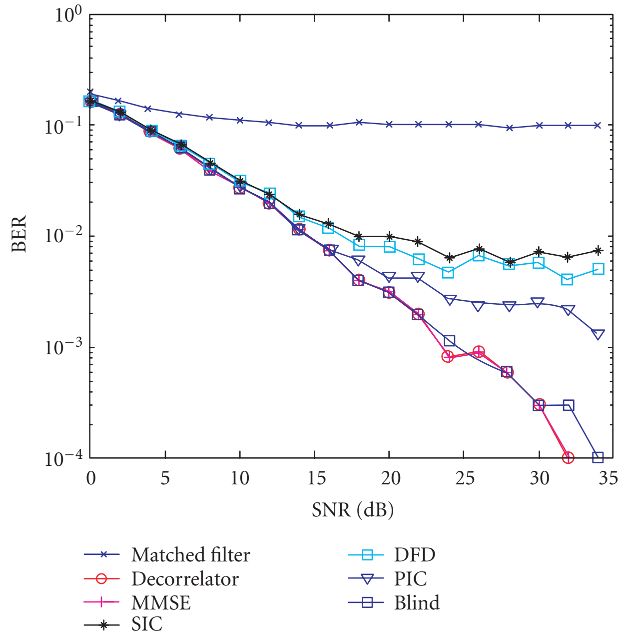

FIGURE 5: BER performance comparison between the proposed blind ICA multiuser receiver and the other receivers in a fast Rayleigh fading channel with the $f_D = 1\,\text{kHz}$, $T_s = 10^{-2}$, number of the users, $K = 10$, processing gain, $N_{PG} = 127$.

blind ICA-based receiver follows closely the performance of the *training-based* MMSE and decorrelating detectors.

Example 2. This example examines the performance of the different detectors in a fast (flat-) fading environment, as shown in Figures 5, 6, 7, and 8 for a processing gain of $N_{PG} = 127$ and $N_{PG} = 15$, doppler bandwidth, $f_D = 1\,\text{kHz}$ and $f_D = 100\,\text{Hz}$. The proposed blind ICA detector exhibits nearly equivalent performance to that of the MMSE and decorrelating detectors and at high SNRs outperforms the alternative multiuser detectors PIC, DFD, and SIC. The PIC detector showed the best performance at high SNRs. This is because of the frequent use of signature waveforms to deal with changing levels of MAI. Again, the conventional matched-filter receiver showed relatively poor ability to deal with multiple-access interference.

5. DISCUSSION

A blind multiuser detector based on blind source separation has been proposed for CDMA systems over Rayleigh flat-fading channels. This detector applies an iterative decision-aided procedure to reconstruct the unmixing matrix and the distorted signals from the input data. Simulation studies have shown that the proposed blind ICA multiuser receiver outperforms other more conventional blind multiuser detectors, and achieves nearly the same performance of the ideal training-based MMSE receivers under severe environmental conditions. The main advantage of the proposed receiver over the investigated alternatives is that it does not require the training sequence.

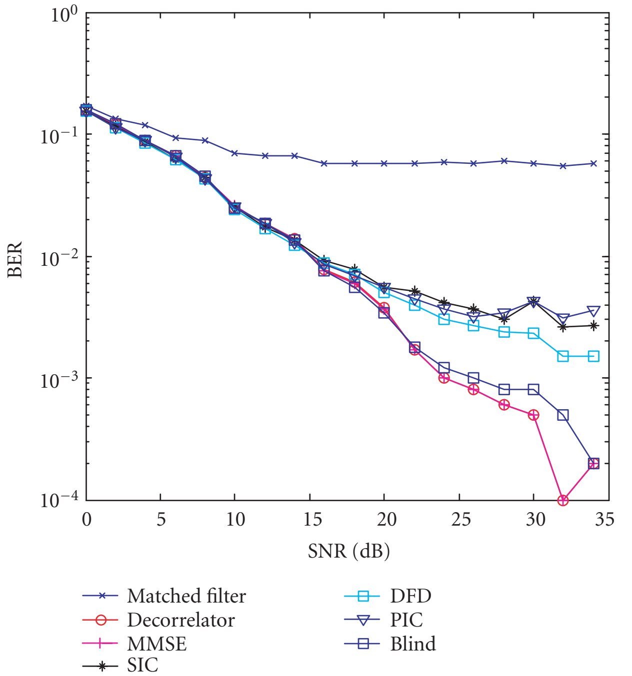

FIGURE 6: BER performance comparison between the proposed blind ICA multiuser receiver and the other receivers in a fast Rayleigh fading channel with the $f_D = 1\,\text{kHz}$, $T_s = 10^{-2}$, number of the users, $K = 10$, processing gain, $N_{PG} = 31$.

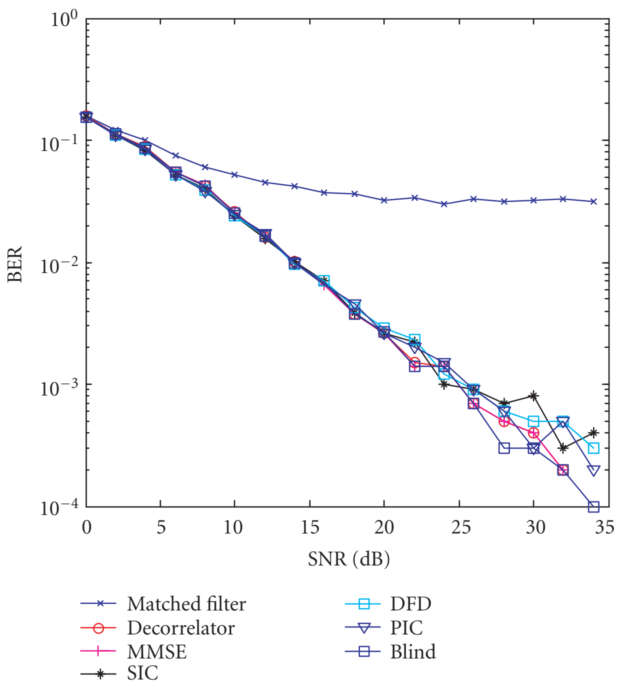

FIGURE 7: BER performance comparison between the proposed blind ICA multiuser receiver and the other receivers in a fast Rayleigh fading channel with the $f_D = 100\,\text{Hz}$, $T_s = 10^{-2}$, number of the users, $K = 10$, processing gain, $N_{PG} = 127$.

The main reasons for considering ICA as an additional tuning element in the next-generation CDMA system are as

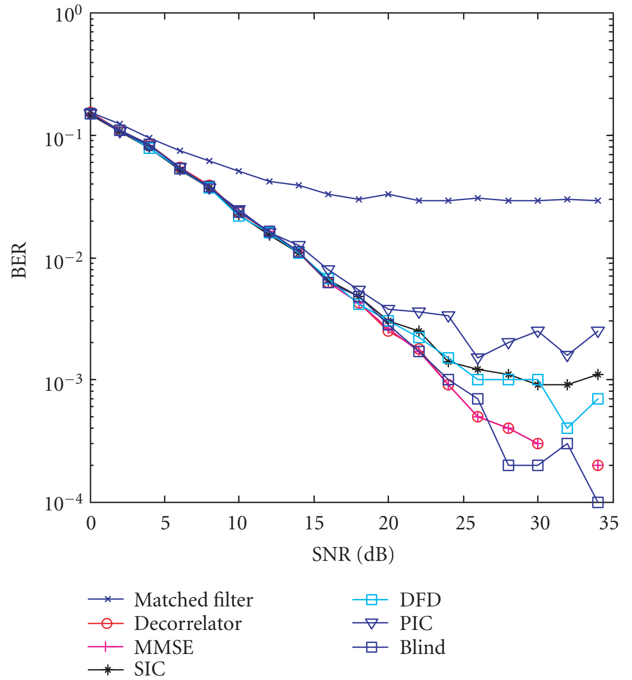

FIGURE 8: BER performance comparison between the proposed blind ICA multiuser receiver and the other receivers in a fast Rayleigh fading channel with the $f_D = 100\,\text{Hz}$, $T_s = 10^{-2}$, number of the users, $K = 10$, processing gain, $N_{PG} = 31$.

follows.

(i) The conventional CDMA detection and estimation methods do not exploit the powerful but realistic independence assumption [15]

(ii) ICA offers an additional interference suppression capability, since the independence of the source signals is utilized [7].

(iii) ICA is worth considering as an additional element, attached to the existing matched filter-based CDMA receiver structure.

6. CONCLUSION

We have proposed and analyzed a blind multiuser detector based on ICA algorithm. The proposed blind multiuser detector has the potential to replace the conventional MMSE detector which requires training sequences and knowledge of the original transmitted signals. This way, the proposed blind ICA multiuser detector is suitable for the next-generation wireless CDMA communication system. Several simulation results show that the blind multiuser detector provides significant performance improvements over other multiuser detectors.

Nomenclature

AWGN	Additive white Gaussian noise
BER	Bit error rate
BPSK	Binary phase-shift keying
BSS	Blind source separation

CDMA	Code-division multiple access
DFD	Decision-feedback detector
FDMA	Frequency-division multiple access
ICA	Independent component analysis
ISI	Intersymbol interference
MAI	Multiple-access interference
MMSE	Minimum mean-square error
PCA	Principle component analysis
PIC	Parallel interference cancellation detector
sgn	Signum operator
SIC	Successive interference cancellation detector
SNR	Signal-to-noise ratio
TDMA	Time-division multiple access

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REFERENCES

[1] M. Honig, U. Madhow, and S. Verdu, "Blind adaptive multiuser detection," *IEEE Transactions on Information Theory*, vol. 41, no. 4, pp. 944–960, 1995.

[2] S. Verdu, "Adaptive multiuser detection," in *Proceedings of IEEE 3rd International Symposium on Spread Spectrum Techniques and Applications (IEEE ISSSTA '94)*, vol. 1, pp. 43–50, Oulu, Finland, July 1994.

[3] P. Patel and J. Holtzman, "Analysis of a simple successive interference cancellation scheme in a DS/CDMA system," *IEEE Journal on Selected Areas in Communications*, vol. 12, no. 5, pp. 796–807, 1994.

[4] R. Kohno, M. Hatori, and H. Imai, "Cancellation techniques of co-channel interference in asynchronous spread spectrum multiple access systems," *Electronics and Communications in Japan*, vol. 66-A, no. 5, pp. 20–29, 1983.

[5] P. He, T. T. Tjhung, and L. K. Rasmussen, "Constant modulus algorithm CMA for CDMA communications," in *Proceedings of 48th IEEE Vehicular Technology Conference (VTC '98)*, vol. 2, pp. 949–953, Ottawa, Ontario, Canada, May 1998.

[6] D. Samardzija, N. Mandayam, and I. Seskar, "Blind successive interference cancellation for DS-CDMA systems," *IEEE Transactions on Communications*, vol. 50, no. 2, pp. 276–290, 2002.

[7] T. Ristaniemi and J. Joutsensalo, "Advanced ICA-based receivers for block fading DS-CDMA channels," *Signal Processing*, vol. 82, no. 3, pp. 417–431, 2002.

[8] A. Hyvarinen and E. Oja, "A fast fixed-point algorithm for independent component analysis," *Neural Computation*, vol. 9, no. 7, pp. 1483–1492, 1997.

[9] X.-D. Zhang and W. Wei, "Blind adaptive multiuser detection based on Kalman filtering," *IEEE Transactions on Signal Processing*, vol. 50, no. 1, pp. 87–95, 2002.

[10] S. Verdu, "Multiuser detection," in *Code-Division Multiple-Access Channels*, chapter 2, Cambridge University Press, Cambridge, UK, 2nd edition, 2001.

[11] A. Hyvarinen and E. Oja, "Independent component analysis: a tutorial," Tech. Rep., Helsinki University of Technology, Espoo, Finland, April 1999.

[12] P. Comon, "Independent component analysis, a new concept?" *Signal Processing*, vol. 36, no. 3, pp. 287–314, 1994, Special issue on Higher-Order Statistics.

[13] H. Delic and A. Hocanin, "Robust detection in DS-CDMA," *IEEE Transactions on Vehicular Technology*, vol. 51, no. 1, pp. 155–170, 2002.

[14] S. Buzzi, M. Lops, and H. Vincent Poor, "Code-aided interference suppression for DS/CDMA overlay systems," *Proceedings of the IEEE*, vol. 90, no. 3, pp. 394–435, 2002.

[15] A. Hyvarinen, J. Karhunen, and E. Oja, *Independent Component Analysis*, John Wiley & Sons, Toronto, Canada, 2001.

[16] S.-I. Amari, "Natural gradient works efficiently in learning," *Neural Computation*, vol. 10, no. 2, pp. 251–276, 1998.

[17] R. R. Coifman and D. L. Donoho, "Translation-invariant de-noising," Tech. Rep., Yale University and Stanford University, New Haven, Conn, USA, 1995.

[18] A. Hyvarinen, J. Karhunen, and E. Oja, "Principal component analysis and whitening," in *Independent Component Analysis*, pp. 125–144, John Wiley & Sons, New York, NY, USA, 2001.

[19] S.-I. Amari, "Stability analysis of adaptive blind source separation," Tech. Rep., Brain Information Processing Group, 1997.

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