CHAPTER 6
THE PROPOSED SYSTEM MODEL

In this chapter a new hybrid scheme of reception is proposed for the blind reception of multiuser CDMA signals in a linear multi-input multi-output (MIMO) scenario. The receiver is assumed to have only the knowledge of only the spreading code of interest. The chapter brings out a two-step adaptive reception method. The first step separates the user signals without explicit channel estimation. A higher order statistical (HOS) approach for the blind separation of the user signals is employed. This is followed by the adaptive detection based on the principle of minimum output energy (MOE). The proposed technique is found to be well suited to the problem of blind MUD reception since no previous knowledge about the signal or propagation channel characteristics is required. The blind source extraction is implemented using a simple feed forward ANN configuration.

6.1 INTRODUCTION

Blind multiuser detection for CDMA channels has been a hot topic of interest for a long time. This is particularly because of two main reasons. First, in actual case, the receiver need not have any knowledge of the channel of propagation or of the signals except for the spreading codes. Second, the bandwidth available can be better utilized, avoiding the need for any training or pilot signals.

Independent Component Analysis (ICA) is a method for finding the underlying components from a multivariable or multidimensional statistical data. This topic is gaining more attention in the present signal analysis scenario. The peculiar property of this method is that it separates out statistically independent signals effectively. This aspect is particularly important in the case of digital communication.

Code Division Multiple Access implemented with DS Spread Spectrum (DS-SS) modulation is much popularity in multiple access communication. Various blind multiuser detection techniques are discussed in the literature [18]. These include the Direct Matrix Inversion (DMI), Least Mean Square (LMS), Recursive Least Squares (RLS), and subspace blind detectors. Various adaptive methods are also cited for multipath cases [18]. Results of Bit Error Rate (BER) analysis of RAKE structure has
been reported [53]. These algorithms perform well under perfect power control. Still the Near Far problem is of much concern in most real situations. In most of the cases the channel estimation seems to be the major issue. Recently some approaches have been reported which perform direct detection without any channel estimation [54] where a subspace technique along with only the spreading code of the user is employed. Other studies include a blind Adaptive Minimum Variance CDMA Receiver [55], Blind Multiuser Detection via Interference Identification [56], Successive Interference Cancellation Iterative Least Squares [57], Blind Multiuser Detection with Partially Adaptive GSC Structure in Space-Time Coded CDMA systems [58] and Blind Space-time Receivers [59]. Blind receivers using the PARAFAC method has also been cited [60].

The idea of Blind Source Separation (BSS) of linearly mixed signals is now under extensive research [37]. BSS relies on only very weak assumptions on the signals and the mixing process (hence the “blind” descriptor) and this blindness enables the technique to be used in a wide variety of situations. This has the advantage that it can be easily optimized for specific problems. The ICA technique is being widely used under the De-noising Source Separation (DSS) framework [35][36],[61],[62]. Independent Component Analysis has been under much study and use in the field of bio-signal analysis, especially brain signals [61],[62]. This technique essentially assumes and utilizes the statistical independency of the signals under consideration. This proves to be definitely a good technique for the reception of digital signals where the transmitted signals are statistically independent.

Within Blind Source Separation research there are two important problems that are generally considered: instantaneous BSS and convolutive BSS. The difference between these two is based on the nature of the signal mixing process; in essence instantaneous BSS separates signals that are mixed without introducing time delays whereas convolutive BSS can achieve separation when time delays are involved.

The proposed scheme does essentially the blind separation of the desired signal using the ICA method. The separated signal is detected using the various known popular techniques. The simulation results show extremely good performance in Bit Error Rate (BER), convergence and Near Far Resistance (NFR).
An artificial neural network (ANN), also called a simulated neural network (SNN) or commonly just neural network (NN) is an interconnected group of artificial neurons that uses a mathematical or computational model for information processing based on a connectionist approach to computation. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network. Artificial neural networks are designed to model some properties of biological neural networks, even though most of the applications are of technical nature. The utility of artificial neural network models lies in the fact that they can be used to infer a function from observations. This is particularly useful in applications where the complexity of the data or task makes the design of such a function by hand impractical. Properties of the ANN such as trainability, non-linear nature, MIMO capability, interpolation capability, fault tolerance and speed of response makes it highly suitable for complex signal processing. It is well suited to processes where deterministic methods fail because of speed or accuracy, or because of lack of process knowledge.

6.2 THE MULTIUSER SYSTEM MODEL

The proposed system considers a K user synchronous system in a small scale flat fading space time scenario. The transmitted signal is considered to be BPSK modulated. The signals of individual users are assumed to be transmitted synchronously. The ambient noise in the transmission channel, is additive white Gaussian (AWGN).

The system model for a synchronous digital DS-SS CDMA with coherent Binary Phase Shift Keying modulation format can be described by a received signal [18]:

\[ r(t) = \sum_{r=0}^{M-1} \sum_{k=1}^{K} A_k b_k(i) s_k(t - r \tau_b) + n(t) \]  

(6.1)

where \( K \) is the number of active users, \( M \) is the length of data transmitted by each user, \( A_k \) is the amplitude of the component of the received signal from the \( k^{th} \) user, \( b_k(i) \) denotes the \( i^{th} \) bit of the \( k^{th} \) user's message, and \( s_k(t) \) is the signature waveform for the \( k^{th} \) user. This is defined for \( 0 \leq t < T_b \). Here \( n(t) \) is the channel noise added to the DS-SS signal in transmission and \( \tau_b \) is the bit period common to all synchronous users. This general equation may be simplified to represent only the \( i^{th} \) bit of data transmitted as follows:

\[ r(i) = \sum_{k=1}^{K} A_k b_k(i) s_k + n(i) \]  

(6.2)
where \( n(i) \) is a length \( N \) vector of noise samples generated for the \( i^{th} \) bit transmitted. This equation for the \( i^{th} \) received bit may then be represented in matrix form (indicated by bold letters):

\[
r(i) = SAb(i) + n(i)
\]  
where \( r(i) \) is a length \( N \) vector of representing the \( i^{th} \) bit transmitted, \( S \) is the \( K \times N \) code matrix, comprised of the length \( N \) signature sequences for each of the \( K \) users, \( A \) is a \( K \times K \) diagonal matrix of user amplitudes such that \( A = \text{diag}(A_1, \ldots, A_K) \), \( b(i) \) is the length \( K \) vector of the \( i^{th} \) bits transmitted by each user, \( n(i) \) is a length \( N \) vector of noise samples generated for the \( i^{th} \) bit transmitted.

Key assumptions in CDMA system model adopted here are:

- The receiver has perfect knowledge of signature sequences of all \( K \) users for the successful recovery or detection of the transmitted signals.
- The sequence of noise samples is a sequence of independently and identically distributed random (i.i.d) variables with Gaussian distribution.

### 6.3 MIMO SYSTEM MODEL

In Multi-Input Multi-Output (MIMO) channels blind signal separation tries to estimate the unobservable sources, or the mixing system (e.g. the channel), or its inverse system, without explicit knowledge of the mixing system or the transmitted signals. Knowledge of the statistical and structural properties of the sources or mixing parameters is exploited in the process. Source signals are assumed to be statistically independent, and the mixing system is assumed to be linear. The mixing may be instantaneous or convolutive. Instantaneous mixing leads to an I-MIMO system model, whereas convolutive mixing with Finite Impulse Response (FIR) filters may be described using FIR-MIMO model.

Consider a system with \( K \) users employing normalized spreading waveforms \( s_k(t), k=1,\ldots,K \) and transmitting sequences of Binary Phase Shift Keying (BPSK) symbols through their respective multipath channels. The transmitted baseband signal of the \( k^{th} \) user is given by [18]

\[
x_k(t) = A_k \sum_{i=0}^{M-1} b_k[i] s_k(t - iT), k = 1,\ldots,K,
\]  

(6.4)
where $M$ is the number of data symbols per user per frame, $T$ is the symbol interval, $b_{k[i]} \in \{+1,-1\}$ is the $i^{th}$ symbol transmitted by the $k^{th}$ user, and $A_k$ the amplitude of the $k^{th}$ user.

It is assumed that $s_k(t)$ is of unit energy, periodic and supported only in the interval $[0,T]$. It is of the form

$$s_k(t) = \sum_{j=0}^{N-1} c_{j,k} \psi(t - jT_c), 0 \leq t \leq T, \tag{6.5}$$

where $N$ is the processing gain, $c_{j,k}$ is the signature sequence of the $k^{th}$ user and $\psi$ the normalized chip waveform of duration $T/N$.

At the receiver an antenna array of $P$ elements is assumed. The baseband multipath channel for $k^{th}$ user can be modeled as the single-input multiple-output (SIMO) given by the impulse response

$$g_k(t) = \sum_{l=1}^{L} a_{l,k} \delta(t - \tau_{l,k}), \tag{6.6}$$

where $L$ is the number of paths for each user, $a_{l,k}$ the complex gain, $\tau_{l,k}$ the delay for the $k^{th}$ user and $\vec{a}_{l,k} = [a_{l,k,1}, a_{l,k,2}, \ldots, a_{l,k,P}]^T$ is the array response vector for the $l^{th}$ path of the $k^{th}$ user's signal. Here $g_{k} = [g_{1,k}, g_{2,k}, \ldots, g_{P,k}]^T$ is a complex vector known as the steering vector representing the response of the channel and array to the $k^{th}$ user's signal. For convenience and without loss of generality it can be assumed that the steering vectors are linearly independent. The total received signal at the receive array is the superposition of the signals from all $K$ users plus the additive noise.

$$\vec{r}(t) = \sum_{k=1}^{K} x_k(t) * g_k(t) + \vec{n}(t), \tag{6.7}$$

where $*$ denote convolution and $\vec{n}(t) = [n_1(t), n_2(t), \ldots, n_P(t)]^T$ is a vector of independent zero mean complex white Gaussian process with power spectral density $\sigma^2$.

A sufficient statistic for the reception of the above model is got by passing $\vec{r}(t)$ through $KL$ beamformers (spatial RAKE) followed by an array of temporal matched filters (RAKE). This scheme is equivalent to a Space Time Matched Filter [18].

The following assumptions are also made in this model.

i) The multipath delay between any user–antenna pair is time invariant over $N$ symbols.

ii) No pilot or training sequence is used in the detection process for the adaptation.
For the MIMO case the model is recast as in (6.8) for each receiving antenna. At the 

\[ y_i = g_i \sum_{t=0}^{M-1} \sum_{k=1}^{K} A_k b_k (i)[s_k(t-iT) + n'(t)] \]  

(6.9)

where \( g_i \) approximates the overall effect of the various user-antenna paths, and \( n'(t) \) the associated noise. In matrix form the model representation is:

\[ Y = HS \]  

(6.10)

Here \( Y \) is the \( L \times M \) matrix with each row giving the stream at each antenna, \( H \) the \((L \times L)\) transfer matrix (equivalent to steering vector) of the multipath channel. Each row of the \( L \times M \) matrix \( s \) gives the combined effect of all users’ signals. These row signals will be independent since they are being formed in transit over different independent paths and time with entirely different mixing properties.

Figure 6.1 shows the conventional non blind MIMO system model.

**Figure 6.1: The conventional non blind MIMO system model**

### 6.4 THE PROPOSED SYSTEM MODEL

Figure 6.2 shows the proposed blind receiver model for a MIMO system.

This is a two-step adaptive reception method. The first step separates the user signals without explicit channel estimation. The higher order statistical (HOS) approach of independent component analysis (ICA) is employed for the blind separation of the user
signals (BSS). This is followed by the adaptive detection based on the principle of minimum output energy (MOE). The following sections describe these two steps.

![Proposed System Model](image)

**Figure 6.2 Proposed System (Receiver) Model**

### 6.5 THE ICA METHOD

Blind algorithms are either implicitly or explicitly based on higher-order statistics (HOS), which retain the phase information and allow for identifying both minimum phase and non-minimum phase channels. In the time domain, higher-order statistics are represented by higher-than-second-order cumulants and moments. Their frequency-domain counterparts, obtained by multidimensional Fourier transforms, are called polyspectra and moment spectra. In most higher-order-statistics-based equalization algorithms, the polyccepstrum is employed. Algorithms using higher-order statistics exploit the non-Gaussian nature of communication signals. Gaussian signals are completely defined by their two first moments. Hence, higher-order cumulants and moments quantify the distance from being Gaussian.

Independent Component Analysis (ICA) is a non-linear, statistical computational model [61],[62] that uses linear transformations on multidimensional data to interpret the spectral signatures of the mixed signal. It can be used to compute the hidden factors underlying parallel signals or measurements or time series sets. The technique assumes that the spectral components of the observed mixed signal are statistically independent and provides an unsupervised method for the blind source separation problem. It can also suitably represent multivariate data by its basis functions.
Given a set of observations of random variables \((x_1(t), x_2(t), \ldots, x_n(t))\) where \(t\) is the time or sample index, assume that they are generated as a linear mixture of independent components \(s_i\),

\[ X = As \]  

(6.11)

where \(A\) is some unknown matrix and \(X\) the observation vector. Signal recovery now consists of estimating both the matrix \(A\) and the \(s_i(t)\), when only the \(x_i(t)\) observable. Here it is assumed that the number of independent components \(s_i(t)\) is equal to the number of observed variables; this is a simplifying assumption that is not completely necessary.

Alternatively, ICA is defined as follows: find a linear transformation given by a matrix \(W\) so that the random variables \(y_i(t), i=1,\ldots,n\) are as independent as possible. In other words:

\[ U = WX = WAs \]  

(6.12)

which indicates that estimation of \(A\) gives \(W\) by taking its inverse. The model in (6.12) can be estimated if and only if the components are non-Gaussian [61]. Figure 6.3 depicts the model described above in equations (6.11) and (6.12).

\[ U = WX = WAs \rightarrow DPs \]  

(6.13)
where $D$ is a nonsingular diagonal matrix and $P$ is a permutation matrix. At most one source is allowed to be Gaussian, to ensure the identifiability. The theoretical solutions of the blind-separation problem are commonly based on maximum-likelihood estimation, minimization of mutual information, or infomax [41].

6.6 MINIMUM OUTPUT ENERGY (MOE) DETECTOR

In multiuser CDMA each user has a unique signature quasi-orthogonal to the signatures of the other users. Each complex bit is coded into bit stream using this signature, and transmitted through the communication channel, where it gets mixed with the signals of the other transmitters (user’s signals) and also with some noise caused by multi-path propagation, Doppler shifts, interfering impulsive signals and the like.

At the receiver only the mixed noisy signal and the signature sequence(s) are available. The reception at the receiver is in two steps. First, the sources are separated using the ICA method. The separated bit streams are sequences of ones and zeros corresponding to the signature length. The channel, noise and other interfering factors cause variation of the original transmitted signal. Second, the required user signal is taken out and the bit streams detected to recover the original message. The bits are usually extracted by majority voting. The extracted bits of each stream are then summed to get the original message bit.

The detection of the desired user is done through an adaptive MUD algorithm [19]. The blind MUD approach is based on decomposing the linear MUD filter response (canonical representation) into two orthogonal components. One of the components is equal to the signature waveform of the desired user. Consider the linear detector of user 1 which is characterized by the filter response $c_1$, the symbol estimate is

$$b_{\text{hat}1} = \text{sgn}(<y,c>)$$

where

$$c_i = s_i + x_i$$

$$<s_i,c_i> = 0$$

Here $s_1$ is the signature waveform of user 1 which is known. The orthogonal component of the given linear transformation $d_1$ is given by

$$x_1 = \frac{1}{<c_i,d_i>} * d_i - s_i$$

Thus
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\[ b_{\text{hat}1} = \text{sgn}(<y,s_i + x_i>) \]

(6.18)

Also

\[ b_{\text{hat}1} = \text{sgn}(A_i b_i + \sum_{k=2}^{K} A_k b_k (\rho_{ik} + <s_k,x_{i1}>) + n_i) \]

(6.19)

where \( \rho_{ik} \) is the cross-correlation of the signature sequences of the users.

\[ E\{(<y,s_i + x_i>)^2\} = A_i^2 + \sum_{k=2}^{K} A_k^2 (\rho_{ik} + <s_k,x_{i1}>)^2 + N_0 (1 + \|x\|^2) \]

(6.20)

Here the used fact is that the bits of user \( i \) are uncorrelated with the bits of the other users and the noise. The first term in (6.20) is the signal energy and the two other terms represent the interference energy (MAI + noise). Due to the canonical representation it can be seen that the signal energy is transparent to the choice of \( x_i \). Choosing \( x_i \) to minimize the output energy would just minimize the interference energy. The variance at the output of the linear transformation in (6.18) is the output energy of this minimum output energy (MOE) detector and is given by

\[ \text{MOE}(x_{i1}) = E\{(<y,s_i + x_{i1}>)^2\} \]

(6.21)

The Mean Square Energy (MSE) is

\[ \text{MSE}(x_{i1}) = E\{(A_i b_i - <y,s_i + x_{i1}>)^2\} \]

(6.22)

That is [19],

\[ \text{MSE}(x_{i1}) = \text{MOE}(x_{i1}) - A_i^2 \]

(6.23)

It is seen that (6.21) and (6.22) differs only by a constant. That is, minimizing both the functions are the same. Here no training sequence is required to implement the gradient descent algorithm (since the MOE does not depend on the data). Thus an adaptive MMSE detector results without the need for any training sequence. This is the basis for the blind adaptive multiuser detector. The steepest descent algorithm is used to derive the update rule for the adaptive algorithm. It is needed to just update the orthogonal component to \( s_1 \) to obtain the minimum of the MOE by changing just \( x_i \).

The update rule is given by:

\[ x_i[i] = x_i[i-1] - \mu Z[i](y[i] - Z_{\text{mf}}[i]s_i) \]

(6.24)

where \( Z_{\text{mf}} \) is the matched filter estimate of the symbol concerned and \( \mu \) the step size.

Figure 6.4 shows the schematic representation of (6.24).
6.6.1 Advantages of MOE Detector

The benefits of using the MOE-based linear blind multiuser detectors are

- Due to its LMS-like adaptation, the MOE algorithm in (6.24) has low computational complexity.
- Since the MOE cost function in (6.21) is strictly convex (i.e., quadratic cost), its adaptation in (6.24) is globally convergent and avoids any ill convergence problems. That is, it converges to the desired minimum, regardless of its initialisation.

![Diagram of linear MUD](image)

Figure 6.4 The canonical representation of linear MUD

- In deriving (6.23), the received signal model of the DS-CDMA system have not been used, and the only assumption used is that the desired bit $b_1[i]$ is uncorrelated with the MAI. Since the MOE cost is related to the MSE cost by a constant, the MOE detector converges to the linear MMSE detector. Hence minimising MOE also minimizes MSE and the near far resistance of the converged MOE solution approaches that of the MMSE detector [19].

## 6.7 SOURCE SEPARATION USING NEURAL NETWORK

In the domain of unsupervised neural learning, ICA is rapidly emerging as a means for performing blind source retrieval or recovery (BSR). This process involves estimating the independent components in data. This data mining approach regards ICA as a method of presenting the data in more comprehensible way by revealing the hidden structure in the data and often reducing the dimensionality of the representation.

Theoretically, ICA should be useful in quite all applications which are based on the assumption of mutual independence between sources (very plausible in real world)
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particularly in the case of physically separated sources. This makes any ICA performing algorithm extremely attractive for data analysis and retrieval.

The infomax criterion \cite{41} is one of the most relevant information-theoretic unsupervised learning rules for neural networks. In order to describe how this idea is applied in the context of BSS, let us consider the neural network presented in Figure 6.3. The Infomax-based training relies on the maximization of the information transferred between x and u, which, for the BSS model, culminates in the maximization of the joint entropy of u. This idea can be expressed by the following optimization problem

\[
\max_{\mathbf{u}} H(\mathbf{u}) \equiv \max_{\mathbf{u}} \mathbb{E} \left\{ \log(\mathbf{g}(\mathbf{w}, \mathbf{x})) \right\} + \log(\det(W))
\]  

(6.25)

where \(g_i()\) corresponds to the \(i\)th activation function.

The first efficient solution to the BSS problem was conceived from the infomax idea. Bell and Sejnowski proposed \cite{63} an adaptive learning algorithm that maximizes the information passed through neural networks. It was proved that a neural network is capable of resolving the independent components in the inputs, that is, the neural network can perform independent component analysis. The main idea is that maximizing the joint entropy \(H(\mathbf{u})\) of the outputs of a neural processor can approximately minimize the mutual information among the output components.

By performing the optimization of (6.25) through the application of the steepest descent method, Bell and Sejnowski \cite{63} derived an algorithm that is extremely simple to implement, and yet permits the separation of a great number of sources. Mathematically, the Bell-Sejnowski (BS) algorithm is described by the following learning rule,

\[
W \leftarrow W + \mu \{ \mathbb{E} \{ G(Wx)x^T \} + WW^T \}^{-1}
\]

(6.26)

where \(\mu\) corresponds to the step size and \(G(\cdot) = [G_1(\cdot) \ldots G_N(\cdot)]\) is a vector of functions such that \(G_i(x) = \frac{d\log(g_i'(x))}{dx}\). If the expectation is omitted in this expression, one readily obtains the online version of the BS algorithm.

The assumptions made for the successful blind separation using ICA method are

- The sources are “statistically independent” of one another.
- The channel can be instantaneous or convolutive and the matrix \(A\) is assumed to be invertible.
• The number of sensors \( n \) is greater than or equal to the number of the sources \( m \). However, it has been shown that in some applications, the number of sources can be greater than the number of sensors.
• At most one source is normally distributed. This is only for the noise-free model
• The mixing matrix \( A \) is full rank.
• Sources are zero mean and stationary.
• The noise \( n(t) \) is white and Gaussian.

**Feed forward artificial neural networks** (FNN) form a class of flexible and widely applied neural models, used to find the relation between the input and the output variables. The problem can be stated as finding a function such as to obtain an estimate of the output values \( y \) from the input values \( x \). The neural network approach of performing prediction is to induce this function in a standard Multi Layer Perceptron (MLP).

The feed-forward networks allow signals to travel one way only; from input to output. There is no feedback (loops) that means that the output of any layer does not affect that same layer. Feed forward networks tend to be straight forward networks that associate inputs with outputs. They are extensively used in pattern recognition [64]. This type of organization is also referred to as bottom-up or top-down.

An important application of neural networks is pattern recognition; it can be conveniently implemented by using a feed forward neural network that has been trained previously. During the training, the network is trained to associate outputs with input patterns. When the network is used, it identifies the input pattern and tries to output the associated output pattern. The power of neural networks comes to life when a pattern that has no output associated with it, is given as an input. In this case, the network gives the output that corresponds to a taught input pattern that is least different from the given pattern.

Bell and Sejnowski noted that [65] many real-world analog signals including the speech signals are super-gaussian and satisfies the independence condition assumed if the transfer function of the neurons in the neural network is a sigmoidal or hyperbolic tangent function. The learning rule for a single layer feedforward neural network to implement the separation is

\[
\Delta W \propto [W^T]^{-1} + (1 - 2y)x^T
\]  

(6.27)
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\[ \Delta w_0 \propto 1 - 2y \quad (6.28) \]

where \( y = f(Wx + w_0) \) and \( f(u) \) is a sigmoid contrast function, usually

\[ f(u) = (1 + e^{-u})^{-1} \quad \text{or} \quad f(u) = \tanh(u) \quad (6.29) \]

A similar learning algorithm was derived by Amari et al. [65] using the natural gradient in the parameter space instead of the descent gradient. This learning rule is

\[ \Delta W \propto [I - f(u) \cdot u^T] \cdot W' \quad (6.30) \]

where

\[ f(u) = \frac{3}{4} x^{11} + \frac{25}{4} x^9 - \frac{14}{3} x^7 - \frac{47}{4} x^5 + \frac{29}{4} x^3 \quad (6.31) \]

This rule speeds up the algorithm by removing the computationally expensive matrix inversion in (6.27).

Figure 6.5 shows the role of ANN in the proposed system (receiver) implementation.

A simple feed forward neural network is employed to generate the de-mixing matrix meant for the source separation. The FNN is trained before use. The training is done using different random as well as deterministic signals. Once the set of weights are converged the network (weights) is used for the source separation. Thus the training being off line, the computational time and complexity can hardly affect the overall performance of the system.
The following are the major factors which influenced the choice of the proposed technique for this work.

- The field of telecommunication especially wireless mobile communication has been experiencing an explosive growth which will definitely continue in future also.
- The available frequency spectrum is a scarce resource; demanding a judicious and better utilization.
- Considerable amount of research work in the area of communication is currently going on for such techniques for the exploitation of the time, frequency and spatial domains.
- Spread spectrum technology with its inherent advantages of resistance to interception, interference, and jamming effects is a good choice as a secure technique for mobile communication.
- The spread-spectrum multiple access system, commercially known as CDMA is emerging as the driving technology behind the rapid advancement of the wireless communication industry. This multiple access technique permits a number of independent users sharing a common channel.
- The use of multiple antennas (MIMO techniques) for wireless communications produces significant performance improvements, including the reduction of bit error rates and the increase of data rates and capacity. Such multiple antenna systems can be combined with linear multiuser detectors to enhance the performance of a DS-CDMA system.
- Blind reception / detection techniques offer better utilization of the channel bandwidth bearing much relevance in the modern communication era.
- The fact that blind algorithms are either implicitly or explicitly based on higher-order statistics (HOS) methods (such as ICA, BSS, BSE) which exploit the non-Gaussian nature of communication signals can be well utilized in the reception process.
- Multiuser CDMA is being considered as the standard for the forthcoming fourth generation wireless communication technologies providing in part, large capacity and more flexibility in multiuser detection.
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- The MOE algorithm which needs only the user codes of interest has low computational complexity as a detection algorithm.
- The adaptive learning property of artificial neural network can be well employed for the implementation of a blind adaptive multiuser detector.

Thus a communication scheme employing a combination of spread spectrum methodologies along with MIMO techniques, blind source extraction, and linear MUD (MOE) would prove to be a good choice for the growing wireless mobile systems.