Minimum BER Criterion Based Robust Blind Separation for MIMO Systems

Zhongqiang Luo, Wei Zhang, Lidong Zhu and Chengjie Li

***Abstract*—In this paper, a robust blind source separation (BSS) algorithm is investigated based on a new cost function for noise suppression. This new cost function is established according to the criterion of minimum bit error rate (BER) incorporated into maximum likelihood (ML) principle based independent component analysis (ICA). With the help of natural gradient search, the blind separation work is carried out through optimizing this constructed cost function. Simulation results and analysis corroborate that the proposed blind separation algorithm can realize better performance in speed of convergence and separation accuracy as opposed to the conventional ML-based BSS.**

***Index Terms*—Blind Source Separation; Cost Function; Bit Error Rate; Maximum Likelihood; Natural Gradient**

I. Introduction

In the past few years, as a paradigm of unsupervised learning in machine learning, blind source separation (BSS) has played an increasingly important role in wireless communication systems for performance enhancement and intelligent information processing [1-14]. It contributes significantly to achieve high spectral efficiency, adaptive signal processing and anti-interference requirements due to its blind feature and statistical information utilization. By virtue of BSS technique, on the one hand, frequently used pilot sequences can be eliminated for enhancing spectral efficiency. On the other hand, it can improve the capacity of the source recovery and resist unpredictable interference in spite of little prior information acquired in advance. In wireless communication systems, a number of received models can be structured as a BSS framework, such as CDMA (code division multiple access) [4-6], OFDM (orthogonal frequency division multiplexing) [7-10] and MIMO (Multiple Input Multiple Output) [11-14], and so on. Generally speaking, those received models can be considered as mixtures of independent source and unknown channel. The expected signals can be separated or extracted from the received mixed signals by using the independent component analysis (ICA) algorithm based BSS technique.

In a general way, the ICA algorithms are composed of two steps. First, the cost function is built based on an independent principle. Second, the cost function is optimized for blind separation. Therefore, it is vital for constructing the cost function and implementing optimizing scheme. There are three popular independent principles based cost function, which includes maximum likelihood (ML), minimum mutual information (MMI) and non-Gaussian maximization [1, 3], respectively. So far, there has been proposed some famous algorithms based on those independent principles, such as FastICA, JADE, Infomax, and so on. Those algorithms are always directly used to carry out blind separation work in the communication system. They always take no account of the performance criterion of the communication system. In fact, those ignored criteria may be combined with independent principles based cost function to propose a more suitable algorithm for executing blind separation of communication mixed signals.

Taking into account of the communication system, the bit error rate (BER) is a significant performance criterion. In this paper, the idea of a minimum BER criterion incorporated into ML or MMI principle is motivated to build the cost function, and then the natural gradient is used to optimize the built new cost function. Simulation results show the proposed new cost function based blind separation algorithm can lead to better performance in speed of convergence and separation accuracy compared with the original one.

The remainder of the paper is organized as follows. In the Section Ⅱ, the system model of blind source separation is reviewed. The new cost function of ICA and the proposed blind separation algorithm are both described in Section Ⅲ. Simulation results and discussion are presented in Section Ⅳ. Section Ⅴ draws the conclusions.

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II. System model

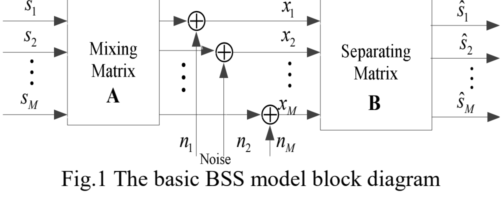

Fig.1 The basic BSS model block diagram

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In this section, the basic BSS model is reviewed. As shown in Fig. 1, the BSS model has a close relationship to MIMO system [1, 14]. Considering the determined BSS model, that is to say, the number of transmitting antennas and receiving antenna is the same in MIMO system. The mutually independent source vector is denoted as $\mathbf{s} = \left(s_1, s_2, \ldots s_M\right)^T$. The mixing matrix is $\mathbf{A}$, which describes a MIMO channel condition. $\mathbf{n} = \left(n_1, n_2, \ldots, n_M\right)^T$ is the noise vectors. The observed mixed signal is $\mathbf{x} = \left(x_1, x_2, \ldots, x_M\right)^T$, in other words, the received signals in MIMO. The received mixed signals can be described as follows,

$$\mathbf{x} = \mathbf{A}\mathbf{s} + \mathbf{n} \tag{1}$$

The goal of BSS is to separate or extract source signals only from observed mixed signals. The source signal estimation can be obtained after the separating operation is executed,

$$\begin{aligned}\hat{\mathbf{s}} &= \mathbf{B}\mathbf{A}\mathbf{s} + \mathbf{B}\mathbf{n} \\ &= \mathbf{s} + \mathbf{B}\mathbf{n}\end{aligned} \tag{2}$$

Ideally, $\mathbf{C} = \mathbf{B}\mathbf{A}$ is an identity matrix, i.e., the separating matrix $\mathbf{B}$ is the inverse of the mixing matrix. In fact, the matrix $\mathbf{C}$ is a generalized permutation matrix due to inherent indeterminacy in BSS. However，this problem has no effect into the separation work.

III. NEW COST FUNCTION FOR BSS

A. ML principle based cost function

The cost function of the ICA problem is usually derived via the maximum likelihood (ML) approach under the independence assumption. Suppose that sources $\mathbf{s}$ are independent with marginal distribution $f_i\left(s_i\right)$.

$$f_{\mathbf{s}}\left(\mathbf{s}\right) = \prod_{i}^{M} f_{s_i}\left(s_i\right) \tag{3}$$

In the linear model, $\mathbf{x} = \mathbf{A}\mathbf{s}$, the joint density of the observation vector is related to the joint density of the source vector as follows:

$$f_{\mathbf{x}}\left(\mathbf{x}\right) = \frac{1}{\left|\det \mathbf{A}\right|} f_{\mathbf{s}}\left(\mathbf{A}^{-1}\mathbf{x}\right) = \left|\det \mathbf{A}^{-1}\right| f_{\mathbf{s}}\left(\mathbf{A}^{-1}\mathbf{x}\right) \tag{4}$$

Then our goal is to find a maximum likelihood estimation of $\mathbf{A}$ (or $\mathbf{B}$ where $\mathbf{B} = \mathbf{A}^{-1}$) to maximize (4). Noting that $\mathbf{y} = \mathbf{A}^{-1}\mathbf{x} = \mathbf{B}\mathbf{x}$, the ML cost function can be derived from the log likelihood of (4) as

$$\log f_{\mathbf{x}}\left(\mathbf{x}\right) = -\log\left|\det \mathbf{A}\right| + \log f_{\mathbf{s}}\left(\mathbf{A}^{-1}\mathbf{x}\right) \tag{5}$$

which can be also written as

$$\log f_{\mathbf{x}}\left(\mathbf{x}\right) = \log\left|\det \mathbf{B}\right| + \log f_{\mathbf{y}}\left(\mathbf{y}\right) \tag{6}$$

$\mathbf{y}$ is the estimation of $\mathbf{s}$ with the actual distribution $f_{\mathbf{s}}\left(\mathbf{s}\right)$ replaced by a hypothesized distribution $f_{\mathbf{y}}\left(\mathbf{y}\right)$. Since sources are assumed to be statistically independent, the cost function is written as

$$J\left(\mathbf{B}\right) = -\log\left|\det \mathbf{B}\right| - \sum_{i=1}^{M} \log f_{y_i}\left(y_i\right) \tag{7}$$

The separating matrix $\mathbf{B}$ is determined by

$$\hat{\mathbf{B}} = \arg\min_{\mathbf{B}} \left\{ -\log\left|\det \mathbf{B}\right| - \sum_{i=1}^{M} \log f_{y_i}\left(y_i\right) \right\} \tag{8}$$

B. Minimum BER constrained ML principle based cost function

In this subsection, the minimum BER criterion is derived firstly. Then the minimum BER criterion incorporated into ML principle based cost function is built. The BSS problem in MIMO is a blind equalization one. Taking into account communication signals in a MIMO system model, the transmitted symbols are equiprobable antipodal symbols (i.e., ± 1, BSPK) uncorrelated with each other, i.e.,

$$E\left\{\mathbf{s}\mathbf{s}^T\right\} = \mathbf{I} \tag{9}$$

The antipodal assumption is made for simplicity, and other constellations can also be used to extend, such as 4-QAM/QPSK. The noise vector $\mathbf{n}$ is zero-mean, white and Gaussian, with covariance matrix

$$E\left\{\mathbf{n}\mathbf{n}^T\right\} = \sigma^2\mathbf{I} \tag{10}$$

When $\mathbf{s}$ is transmitted, $\hat{\mathbf{s}}$, as given by (2), will be the received signal vector. The elements of this vector are then quantized by a threshold detector to obtain $\hat{\mathbf{s}}_q$, whose elements will be ± 1. The average BER of the detected signal is the average of the probability of error of each element of the block, i.e.,

$$P_e = \frac{1}{M} \sum_{m=1}^{M} P_{em} \tag{11}$$

In which P_{em} denotes the BER of the m^{th} source symbol. Since the signal power of each data symbol is unity and the covariance matrix of the received noise is $\sigma^2\mathbf{B}\mathbf{B}^T$, by following standard steps, it can be shown that the probability of the m^{th} source symbol in $\hat{\mathbf{s}}_q$ being in error can be written as

$$P_{em} = \frac{1}{2} erfc\left(\frac{1}{\sqrt{2\sigma^2 \left[\mathbf{B}\mathbf{B}^T\right]_{mm}}} \right) \tag{12}$$

Where, $erfc\left(\varsigma\right) \triangleq \left(2/\sqrt{\pi}\right)\int_{\varsigma}^{\infty} e^{-z^2} dz$, and $\left[\mathbf{B}\mathbf{B}^T\right]_{mm}$ denotes the $\left(m, m\right)^{th}$ element of the matrix $\mathbf{B}\mathbf{B}^T$. The term

$\sigma^2\left[\mathbf{BB}^T\right]_{mm}$ represents the noise variance in the receiver's estimation of the m^{th} source symbol of the transmitted signal vector. Substituting (12) into (11), yielding

$$P_e = \frac{1}{2M}\sum_{m=1}^{M} erfc\left(\frac{1}{\sqrt{2\sigma^2\left[\mathbf{BB}^T\right]_{mm}}}\right) \tag{13}$$

If we assume $\phi(z) = erfc\left(1/\sqrt{2\sigma^2 z}\right)$ for $z > 0$, then

$$\frac{d^2\phi}{dz^2} = \frac{1}{\sqrt{\pi}}\left(2\sigma^2\right)^{-(1/2)}\exp\left(-\frac{1}{2\sigma^2 z}\right)\left(-\frac{3}{2}+\frac{1}{2\sigma^2 z}\right)z^{-(5/2)} \tag{14}$$

Therefore, if $z < 1/3\sigma^2$, then $d^2\phi/dz^2 > 0$. Applying this fact to(13), $\phi\left(\left[\mathbf{BB}^T\right]_{mm}\right)$ is a convex function if the noise power σ^2 is less than $1/3\left[\mathbf{BB}^T\right]_{mm}$. If this condition is satisfied for all m (i.e., if there is sufficiently large SNR at the receiver), the average block BER P_e is also convex [15].

Since P_e is convex at moderate-to-high SNRs, the Jensen's inequality can be applied to obtain the following lower bound on P_e:

$$\begin{aligned} P_e &= \frac{1}{2M}\sum_{m=1}^{M} erfc\left(\frac{1}{\sqrt{2\sigma^2\left[\mathbf{BB}^T\right]_{mm}}}\right) \\ &\geq \frac{1}{2} erfc\left(\frac{1}{\sqrt{\frac{2\sigma^2}{M}\sum_{m=1}^{M}\left[\mathbf{BB}^T\right]_{mm}}}\right) \\ &= \frac{1}{2} erfc\left(\sqrt{\frac{M}{2\sigma^2 tr\left(\mathbf{BB}^T\right)}}\right) = P_{e,LB} \end{aligned} \tag{15}$$

Equality in (15) holds if and only if $\left[\mathbf{BB}^T\right]_{mm}$ are equal $\forall m \in [1, M]$. The inequality of (15) is valid only when P_e is convex, i.e., when

$$\left[\mathbf{BB}^T\right]_{mm} < \frac{1}{3\sigma^2}, \forall m \in [1, M]$$

The quantity $P_{e,LB}$ in (15) defines a lower bound on the BER P_e. Note that since $erfc(\cdot)$ is a monotonically decreasing function, to minimize $P_{e,LB}$ in (15), we need only minimize $tr\left(\mathbf{BB}^T\right)$. That is to say, the minimum BER criterion can be described as follows:

$$\begin{gathered} \min_{\mathbf{B}} tr\left(\mathbf{BB}^T\right) \\ subject\ to \left[\mathbf{BB}^T\right]_{mm} < \frac{1}{3\sigma^2} \end{gathered} \tag{16}$$

Combined with (7), the new cost function with minimum BER criterion can be obtained,

$$\begin{cases} \arg\min_{\mathbf{B}}\left\{-\log\left|\det \mathbf{B}\right| - \sum_{i=1}^{M}\log f_{y_i}\left(y_i\right)\right\} \\ \min_{\mathbf{B}} tr\left(\mathbf{BB}^T\right) \\ subject\ to\ tr\left[\mathbf{BB}^T\right] < \frac{M}{3\sigma^2} \end{cases} \tag{17}$$

In order to simplify the above constrained optimization problem (17), considering (7), the new cost function with minimum BER criterion in condition of the moderate-to-high SNRs can be described as a unconstrained optimization problem, i.e.,

$$\hat{\mathbf{B}} = \arg\min_{\mathbf{B}}\left\{-\log\left|\det \mathbf{B}\right| - \sum_{i=1}^{M}\log f_{y_i}\left(y_i\right) + \lambda tr\left(\mathbf{BB}^T\right)\right\} \tag{18}$$

Where λ is a regulation parameter. Then the natural gradient search for optimizing the cost function (18) can be realized for BSS.

C. Optimizing cost function by natural gradient

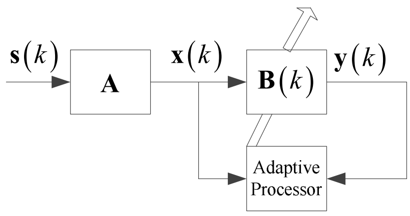


Fig.2 Adaptive processor block diagram

As the previous illustration, the ICA-based blind separation algorithms include a two-step process. The first step is to choose a principle, based on which a cost function is obtained. Next, a suitable method for optimizing the cost function needs to be adopted. In other words, using a cost function converts the blind separation problem into an optimization problem. In this paper, the separation processing is implemented by the adaptive BSS based on the natural gradient for its fast and accurate adaptation behavior. The adaptive processor block diagram for BSS is shown in Fig. 2. For any suitable smooth gradient-searchable the cost function $J(\mathbf{B})$, the natural adaptation is defined as:

$$\mathbf{B} \leftarrow \mathbf{B} - \mu \nabla J(\mathbf{B}) \mathbf{B}^T \mathbf{B} \tag{19}$$

The new built cost function in (18), since the probability density function (PDF) of sources are supposed to be unknown, and $f_{y_i}(y_i)$ is also unknown. Therefore, the activation or score function need be used to approximate probability density function of separation source signals. The function $\varphi_i(y_i)$ denotes the activation or score function in ML approach, which is defined as

$$\varphi_i(y_i) = -\frac{d \log f_{y_i}(y_i)}{dy_i} = -\frac{f'_{y_i}(y_i)}{f_{y_i}(y_i)} \tag{20}$$

Since sources in digital communication are always subgaussian signal, this activation function can be chose as follows [3],

$$\varphi_i(y_i) = -y_i^3 \tag{21}$$

Furthermore we can obtain the gradient of the cost function as follows:

$$\nabla J(\mathbf{B}) = \frac{\partial J(\mathbf{B})}{\partial \mathbf{B}} = -\mathbf{B}^{-T} + \boldsymbol{\varphi}(\mathbf{y})\mathbf{x}^T + 2\lambda \mathbf{B} \tag{22}$$

The natural gradient learning law now yields

$$\mathbf{B} \leftarrow \mathbf{B} - \mu\left(\mathbf{I} - \boldsymbol{\varphi}(\mathbf{y})\mathbf{y}^T - 2\lambda \mathbf{B}\mathbf{B}^T\right)\mathbf{B} \tag{23}$$

IV. SIMULATIONS AND DISCUSSIONS

To demonstrate the effectiveness of the proposed algorithm in this paper, we conduct simulation experiments to evaluate the performance of the proposed ML based cost function with minimum BER criterion by nature gradient (called ML-BER-NG). For comparison, the only ML based cost function by nature gradient (ML-NG) is also illustrated for highlighting the proposed algorithm mechanism by comparative experiments. Considering a MIMO system, the number of transmitting antennas and receiving antennas is 5, the source symbols are from BPSK, the sample size is 4000. The mixing matrix is generated randomly. The performance index is cross talk error. The smaller is this performance index, the better performance is acquired. The cross talk error is defined as following[1, 3]

$$E_{ct} = \sum_{i=1}^{M}\left(\sum_{j=1}^{M}\frac{|c_{ij}|}{\max_k |c_{ik}|} - 1\right) + \sum_{j=1}^{M}\left(\sum_{i=1}^{M}\frac{|c_{ij}|}{\max_k |c_{kj}|} - 1\right)$$

where $\mathbf{C} = \mathbf{BA}$, c_{ij} is element in matrix $\mathbf{C}$. The moderate SNR condition is considered and other parameters setting are same for two methods.

The simulation results are demonstrated in Fig. 3 and Fig. 4, respectively. We can conclude that the proposed cost function by nature gradient can lead to better performance in speed of convergence and separation accuracy. In Fig. 3, we can see that the proposed ML-BER-NG algorithm has low cross talk error and fast convergence rate compared with the original ML-NG algorithm. It is noteworthy that the initial value of a separation matrix is randomly generated, so that the number of iterations is a bit larger. However, the computation complexity is low. It takes just 2-4 seconds to achieve the algorithm convergence from time complexity. From Fig. 4, we can see that BER performance of the ML-BER-NG is better than the ML-NG in moderate SNR condition.

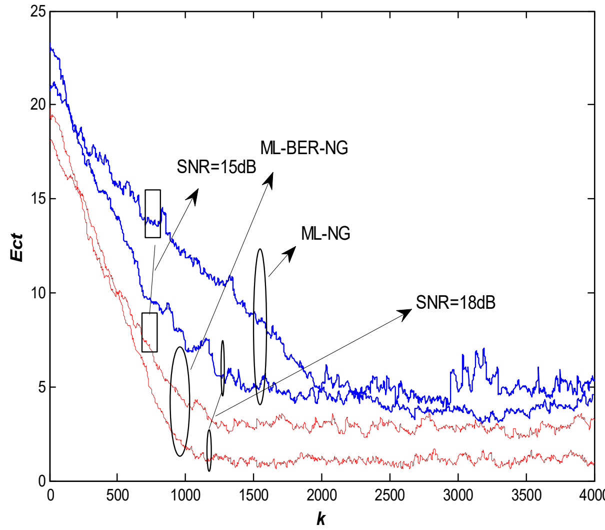


Fig.3 The cross talk error as a function of iterations

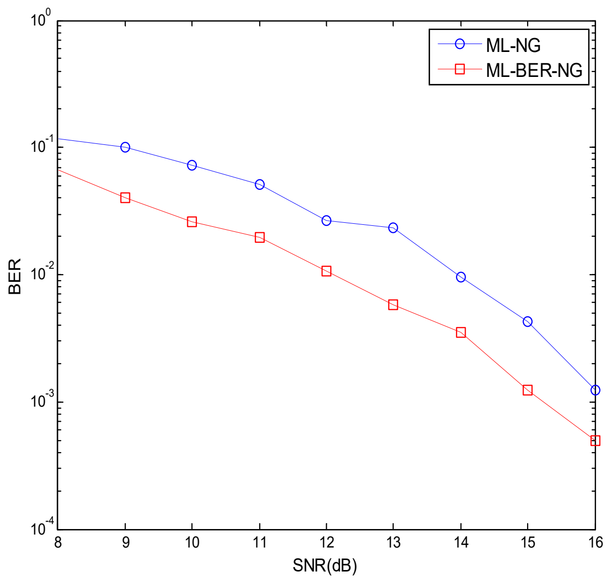
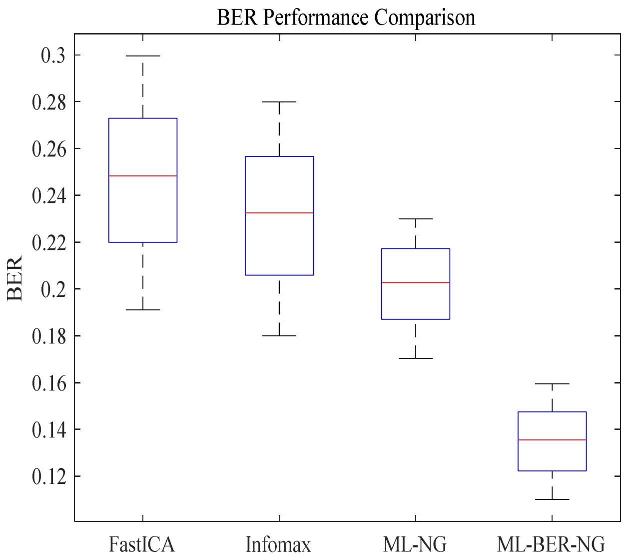
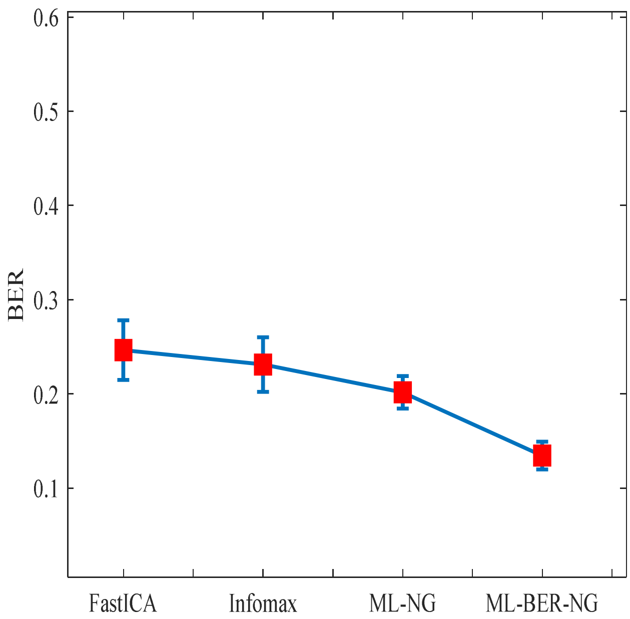


Fig.4 BER performance as a function of SNR

In Fig.5, the further performance comparison of the representative methods is conducted 100 experiments for highlighting the proposed algorithm when the moderate SNR=10dB. In Fig.5(a), the statistical analysis of BER performance is given in a boxplot form, and in Fig.5(b) the BER performance with error bar is drawn to exhibit the performance enhancement of the proposed method compared with other representative algorithms. We can safely obtain that the proposed method achieve the performance refinement in contrast with that of some representative BSS methods for MIMO signals detection.

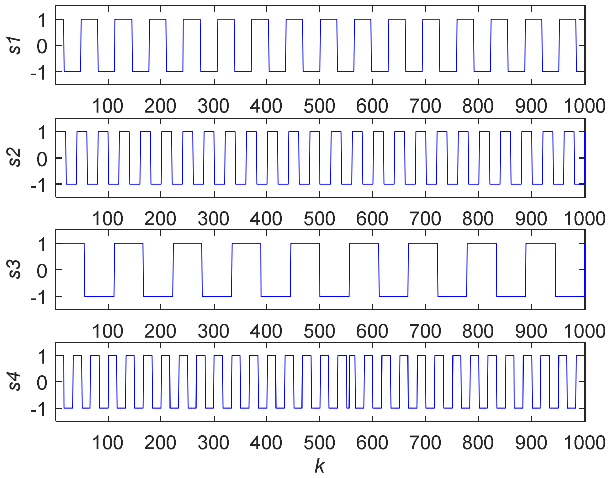


(a)

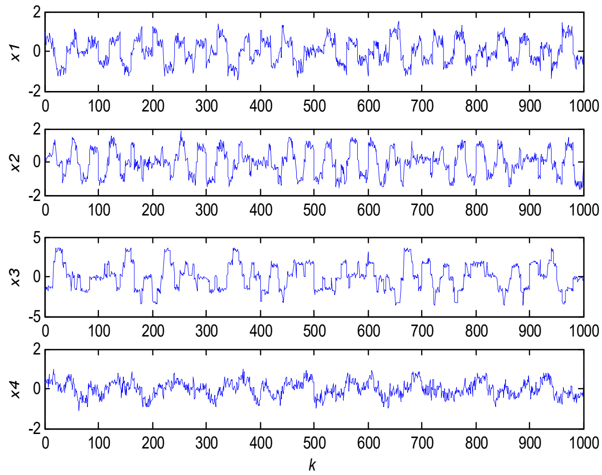


(b)

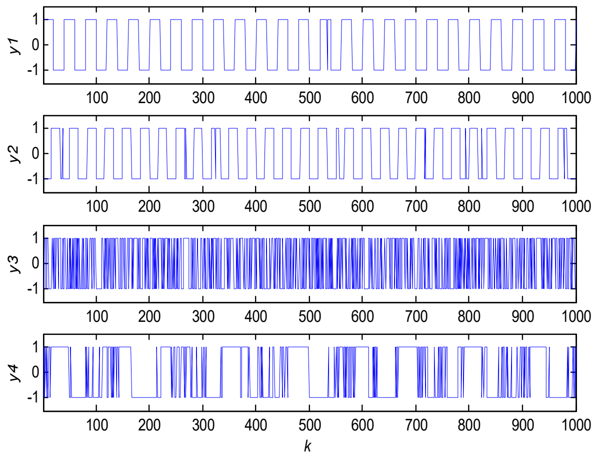
Fig. 5 BER performance comparisons of different representative methods



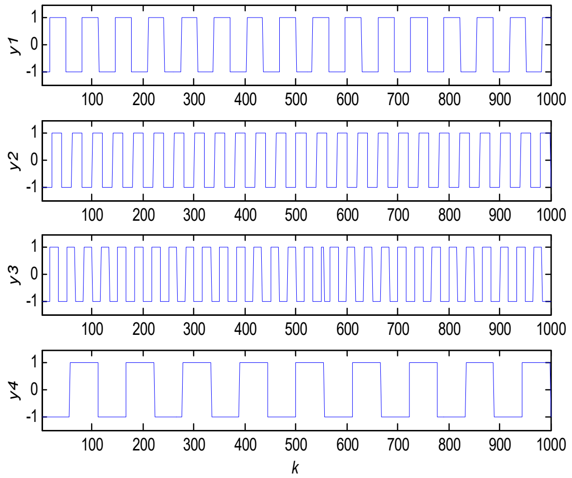
(a) Transmitted signals;



(b) Received mixed signals;



(c) Separated detected signals (ML-NG)



(d) Separated detected signals (ML-BER-NG)

Fig.6 4×4 MIMO; (a) Transmitted signals; (b) Received mixed signals; (c) Separated detected signals (ML-NG) (d) Separated detected signals (ML-BER-NG)

In the next simulation, the direct separation graphs are exhibited for illustration. As shown in Fig.6, it shows the results of blind separation of 4×4 MIMO in SNR=15dB. From the separated results of Fig.6, we can verify that the incorporation of minimum BER criterion in BSS improves the separation performance.

Remarks: The ML principle with minimum BER criterion considers the effect of noise term in the model of the cost function. It is fit for communication signals circumstance. The original ML principle neglects the effect of noise. However, noise is inevitable in a wireless communication environment. Furthermore, the computation complexity of the proposed algorithm (ML-BER-NG) is nearly similar to the ML-NG algorithm with low computation.

V. CONCLUSIONS

In this paper, a minimum BER criterion is considered in combination with the ML independent principle for blind separation problem in MIMO signal detection. The effect of the noise term is taken into account in the process of constructing cost function. The proposed algorithm can lead to better performance in speed of convergence and separation accuracy in moderate SNR condition. It is strongly encouraged to investigate the constrained cost function for BSS problem in low SNR in the future work. It is promising idea for thinking over other communication performance criteria for developing advanced BSS algorithms.

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