Blind Source Extraction From Convolutive Mixtures in Ill-Conditioned Multi-Input Multi-Output Channels

Yuanqing Li, Jun Wang, *Senior Member, IEEE*, and Andrzej Cichocki

***Abstract*—This paper presents a new approach to blind source extraction from convolutive mixtures in multi-input multi-output (MIMO) channels. Two ill-conditioned cases are considered: the number of sensors is less than the number of sources and the number of sensors is greater than or equal to the number of sources but the system is noninvertible. Although there exist several works related to ill-conditioned dynamic MIMO channels, especially on blind channel identification, how to obtain a true source only from observable convolutive mixtures is still an open problem. In this paper, beginning with introducing two blind extraction models for blind deconvolution in ill-conditioned MIMO channels, we discuss the extractability issue. Results from our extractability analysis (a necessary and sufficient condition) show that it is possible to extract individual sources from the outputs. Furthermore, all potentially separable sources (at most equal to the number of sensors) can be extracted sequentially based on these extraction models. A cost function based on cross cumulant is discussed along with the Gauss–Newton algorithm. Finally, a simulation example is presented for illustration.**

***Index Terms*—Blind extraction, convolutive mixtures, extractability, multichannel deconvolution.**

I. Introduction

BLIND deconvolution recovers unknown sources from convolutive mixtures without the information about the signal channels. It has significant potential for applications in numerous technical areas such as array processing, speech and image enhancement, digital communications [1]–[6], to name a few.

Blind deconvolution of multi-input multi-output (MIMO) dynamic channels has received considerable attention in recent years. Many studies on blind deconvolution of MIMO systems have been reported; see the references herein. For example, in [5], [7]–[13], various algorithms (e.g., cumulant-based super-exponential algorithm, adaptive algorithms, Godard cost function, etc.) are developed to recover sources sequentially or simultaneously from convolutive mixtures. [14], [15] explore the geometrical structures of the manifold of finite-impulse response (FIR) filters and develop a natural gradient algorithm for blind deconvolution. Independent component analysis (ICA) techniques has also been used in blind deconvolution. For instance, in [17], several blind source separation (BSS) techniques are extended to blind deconvolution. Most of these studies assume that the number of sources is less than or equal to the number of sensors, and the MIMO system is invertible. From the discussions in [18], we also can see that this assumption plays important roles.

Incidentally, several papers discuss related issues for MIMO static systems with more sources than senors; e.g., [19] and [20]. In [19], by resorting to higher order statistics and multiway array decomposition, it was proved that static MIMO systems with fewer outputs than inputs can be identified; an effective algorithm was proposed to extract three digital sources [e.g., binary phase-shift keying (BPSK) or quadrature phase shift keying (OPSK) sources] from the two observations using the discrete distribution of the sources. Since separability (or extractability) conditions are weaker for a system with digital sources than for analog sources in general [23], the algorithms different from that in [19] should be developed for blind separation or extraction of analog sources from their ill-conditioned mixtures. In [20], it is discussed that the identification of static systems with n sources and two sensors using a joint characteristic function of the random variables (observations); but they did not discuss how to obtain these sources after the systems are identified. In [22], blind identification of multichannel moving average parameter matrices was discussed using higher-order statistics. Five or six assumptions regarding the channels are presented related to channel identification. Similar to [20], there was no discussion about how to estimate the sources.

There exist classical methods for blind separation for ill-conditioned systems with n sources and m sensors (here, $n > m$). That is, only m sources are extracted or separated using general approaches (e.g., in [24]–[26]); the other $n-m$ sources are considered to be noise and are not extracted. In [26], if the system is ill-conditioned (undermodeled case), a local extremum of the criterion only results in a new mixture of several sources. In fact, if an ill-conditioned system is assumed to be an invertible one, and $n - m$ sources are assumed to be noise, then the estimated m signals are, theoretically, new mixtures of $n - m + 1$ sources instead of separated sources, of which the signal-to-noise ratios may be very low.

Blind source extraction is an effective method for recovering sources from instantaneous mixtures in ill-conditioned cases

Manuscript received August 15, 2002; revised February 1, 2004. This work was supported by the National Natural Science Foundation of China under Grant 60004004 including E5303220, the Excellent Young Teachers Program of MOE, China, and by the Hong Kong Research Grants Council under Grant CUHK4203/04E.

Y. Li is with the the Institute of Automation Science and Engineering, South China University of Technology, Guangzhou, 510640, China, with the Laboratory for Advanced Brain Signal Processing, RIKEN Brain Science Institute, Saitama 3510198, Japan, and also with the Institute for Infocom Research, Singapore 119613.

J. Wang is with the Automation and Computer-Aided Engineering Department, The Chinese University of Hong Kong, Shatin, Hong Kong.

A. Cichocki is with the Laboratory for Advanced Brain Signal Processing, RIKEN Brain Science Institute, Saitama 3510198, Japan, and also with the Department of Electrical Engineering, Warsaw University of Technology, Warsaw PL 00 661, Poland.

Digital Object Identifier 10.1109/TCSI.2004.832723

[27]. In this paper, we will show that it is also effective for recovering sources from convolutive mixtures in ill-conditioned MIMO dynamic systems. The aim of this paper is to analyze blind source extraction from convolutive mixtures in ill-conditioned MIMO channels in which the signal channel is not invertible; that is, the number of sources is greater than the number of sensors, or the Z-transform matrix of the system is column-rank deficient when the number of sources is less than or equal to the number of sensors. We present two models and an optimization algorithm to extract sequentially at most m analog sources under extractability conditions. Although theoretically at least $n-m$ sources can not be extracted, the extracted signals are filtered versions of true sources (these sources can then be obtained individually by a [single-input single-output (SISO) deconvolution filter], not the mixtures of one source and the intractable $n-m$ sources.

In the remainder of this paper, we first introduce two blind extraction models for ill-conditioned MIMO dynamic channels, and present the extractability conditions in Section II. The extractability results imply that it is possible to extract an individual filtered source using the two models. Furthermore, all potentially separable sources (at most m) can be theoretically extracted one by one. In Section III, we discuss realization issues of the extraction including a cost function and its corresponding optimization algorithm. Finally, we present an illustrative simulation example in Section IV.

II. Blind Extraction Models and Extractability Analysis

In this section, two blind extraction models are first proposed for blind source extraction in ill-conditioned MIMO dynamic channels. The subsequent extractability analysis demonstrates the theoretical effectiveness of the two models for blind source extraction from convolutive mixtures in ill-conditioned channels.

Consider the blind deconvolution for the following n-input m-output dynamic channel

$$x_i(k) = \sum_{j=1}^{n} h_{ij}(k) * s_j(k), \qquad i = 1, \dots, m \tag{1}$$

where $s_1(k), \dots, s_n(k)$ are n sources at time k, assumed to be independent random sequences with zero means; $x_1(k), \dots, x_m(k)$ are m observed convolutive mixtures; $*$ denotes the linear convolution operator; $h_{ij}(k)$ $(i = 1, \dots, m, j = 1, \dots, n)$ are linear time-invariant filters that may be of nonminimum phase.

In the frequency domain, (1) can be written as

$$X(z^{-1}) = H(z^{-1})S(z^{-1}) \tag{2}$$

where z^{-1} is the delay operator, $S(z^{-1}) = [S_1(z^{-1}), \dots, S_n(z^{-1})]^T$ is the z–transform vector of n source signals, $X(z^{-1}) = [X_1(z^{-1}), \dots, X_m(z^{-1})]^T$ is the z–transform vector of m observed mixtures, $H(z^{-1}) = [H_{ij}(z^{-1})]_{m\times n}$, H_{ij} is the z–transform of h_{ij}, and rational fractions of z^{-1} $(i, j = 1, \dots, n)$, S_j and X_j are polynomials of z^{-1}.

First, we introduce several notations. Define the set

$$G(z) = \left\{ \frac{f(z)}{g(z)} | f(z), g(z) \text{ are real coefficient polynomials of variable } z \right\}.$$

Obviously, $G(z)$ is a field of rational fractions. $\mathcal{G}^n(z)$ denotes the set of n–dimensional vectors with entries in $G(z)$, which is a rational space [31]. $\mathcal{G}^{m\times n}(z)$ denotes the set of $m \times n$ matrices with entries in $G(z)$.

Next, we define an m-input m-output blind extraction model as follows:

$$\begin{aligned} y_i(k) &= \sum_{j=1}^{m} b_{ij}(k) * x_j(k) \\ &= \sum_{j=1}^{m} b_{ij}(k) * \left[\sum_{l=1}^{n} h_{jl}(k) * s_l(k) \right] \\ &= \sum_{l=1}^{n} c_{il}(k) * s_l(k), \qquad i = 1, \dots, m \end{aligned} \tag{3}$$

where $y_1(k), \dots, y_m(k)$ are model outputs in which y_1 corresponds to the extracted source and $y_2, \dots, y_m$ do not contain any source contained in y_1; $b_{ij}(k)$ $(i, j = 1, \dots, m)$ are causal FIR filters; and $c_{il}(k) = \sum_{j=1}^{m} b_{ij}(k) * h_{jl}(k)$. Since the filters h_{ij} in (1) may be of nonminimum phase, b_{ij} should be double-sided.

In the frequency domain, (3) can be written as

$$\begin{aligned} Y(z^{-1}) &= B(z^{-1})X(z^{-1}) = B(z^{-1})H(z^{-1})S(z^{-1}) \\ &:= C(z^{-1})S(z^{-1}) \end{aligned} \tag{4}$$

where $Y(z^{-1}) = [Y_1(z^{-1}), \dots, Y_m(z^{-1})]^T$ is the z–transform vector of $(y_1, \dots, y_m)^T$; $B(z^{-1}) = [B_{ij}(z^{-1})]_{m\times m}$ and $B_{ij}(z^{-1})$ is the z–transform of b_{ij} $(i, j = 1, \dots, m)$.

In fact, the MIMO model (3) or (4) is often used as a separation model for well-posed dynamic channels [25] in which the separation principle is based on mutual independence of all outputs, and all the outputs are separated sources theoretically. In this paper, we use (3) for blind source extraction, where only the first output corresponds to an extracted source signal, the other $m-1$ outputs do not contain any components of the first output, and are considered as new mixtures. The blind extraction principle is based on the pairwise independence of the first output with other $m-1$ outputs. Additionally, we do not use any multiple-input–single-output (MISO) extractor for ill-conditioned dynamic channels. The main reason for this is because it is difficult to establish an optimization criterion with each stable local extremum leading to a single source, as will be discussed in Section III.

In addition to the general extraction filter bank $B(z^{-1})$ in model (4), motivated by the Gaussian elimination procedure, we introduce the nonsingular $B(z^{-1})$ with fewer adaptive parameters than those used in (4), as shown in (5) at the bottom of the next page. Model (4) then becomes

$$\begin{aligned} Y_1(z^{-1}) = X_1(z^{-1}) &- B_{12}(z^{-1})X_2(z^{-1}) \\ &- \cdots - B_{1m}(z^{-1})X_m(z^{-1}) \end{aligned}$$

$$Y_2(z^{-1}) = X_2(z^{-1}) - B_{21}(z^{-1})Y_1(z^{-1})$$
$$\vdots$$
$$Y_m(z^{-1}) = X_m(z^{-1}) - B_{m1}(z^{-1})Y_1(z^{-1}). \quad (6)$$

From the following extractability theorem, we can see that it is possible to extract individual sources from the outputs of an ill-conditioned channel using the above models.

Theorem 1: There exists a full rank matrix $B(z^{-1}) \in \mathcal{G}^{m\times m}(z^{-1})$ such that the first row of $C(z^{-1}) = B(z^{-1})H(z^{-1})$ has p nonzero entries $C_{1l_1}(z^{-1}),\ldots,C_{1l_p}(z^{-1})$ ($1 \le p \le n$, $1 \le l_1 < \cdots < l_p \le n$), and the l_ith ($i = 1,\ldots,p$) column has only one nonzero entry $C_{1l_i}(z^{-1})$ (see (19)), if and only if there exists an $m \times p$ submatrix denoted as $\hat{H}$ composed of p columns of H with rank 1, and the submatrix denoted as $\overset{*}{H}$ composed of the remaining columns satisfies $\mathrm{rank}(\overset{*}{H}) < \mathrm{rank}(H)$. Moreover, each entry of B can be a causal FIR filter.

Proof: See the Appendix.

If H is an $m\times m$ nonsingular matrix or an $m\times n$ rectangular matrix with full column rank, then obviously the conditions of Theorem 1 are satisfied by setting $p = 1$. Consequently, a filtered version of a single source can be extracted. That is to say, the two models above are also suitable for invertible channels.

Remark 1: From the proof of Theorem 1, we can see the following.

1) If $p = 1$, then the extracted signal y_1 is a convolution of the source s_{l_1} and the impulse response of the filter C_{1l_1}. In this case, s_{l_1} is a separable source. If $p > 1$, then y_1 is a new convolutive mixture of some inseparable sources, and $y_2,\ldots,y_m$ do not contain these sources.
2) After a filtered source is extracted, the source can be recovered using a deconvolution algorithm for SISO systems.
3) The number of the sources is not necessarily known. Thus, Theorem 1 is suitable for the case in which the number of sources is unknown.

Remark 2: Model (4) is effective provided that the extractability conditions in Theorem 1 hold. One drawback is that there are many adaptive parameters [$m^2\ell$ where ℓ is the length of every filter in $B(z^{-1})$] that entails extensive computation. Model (6) is less complex than (4) in terms of number of adaptive parameters. As seen in the second part of the proof of Theorem 1 in the Appendix , there always exists a row of H in (1) that satisfies (24) and (25) under the conditions of Theorem 1. If (24) and (25) are satisfied for the first row of H, model (6) can be used. Otherwise, we can exchange X_i (e.g., X_2) and X_1 in (6) and then continue the blind extraction.

In the above theorem, matrix B is assumed to be of full rank. The following theorem shows that the assumption does not affect extractability.

Theorem 2: If there is a row vector (i.e., an MISO extractor) denoted as $B_1(z^{-1}) = [B_{11}(z^{-1}), \ldots, B_{1m}(z^{-1})]$, such that B_1H has only one nonzero entry (without loss of generality, B_1H is denoted as $[g_0(z^{-1}), 0, \ldots, 0]$), then there is a nonsingular $m\times m$ matrix $B(z^{-1}) \in \mathcal{G}^{m\times m}(z^{-1})$ such that only one nonzero entry in the first row and the first column of BH.

Proof: Consider the linear equation with variables $\xi_1,\ldots,\xi_m$

$$H_{11}\xi_1 + H_{21}\xi_2 + \cdots + H_{m1}\xi_m = 0. \quad (7)$$

There are $m-1$ linear independent row vectors that satisfy (7). Based on the conditions in the theorem, $H_{11}B_{11} + \cdots + H_{m1}B_{1m} = g_0$; hence B_1 is independent of all solutions to (7). Thus, we can obtain a nonsingular $m \times m$ matrix B with first row being B_1, and the remaining $m-1$ rows being the $m-1$ linear independent solutions of (7), which satisfies Theorem 2. □

If the mixture matrix $H(z^{-1})$ does not satisfy the conditions in Theorem 1, then, it is impossible to extract any filtered source or a convolutive mixture of several sources using any nonsingular extraction matrix B. Theorem 2 implies that it is also impossible to extract a single source from the mixtures using any $1\times m$ matrix (MISO extractor).

To obtain more than one source, sequential blind extraction can be performed by taking $y_2,\ldots,y_m$ as new inputs of the blind extraction model, similar to (4) or (6). The following theorem implies that we can obtain close to the best result using the sequential blind extraction approach.

Theorem 3: If there are at most q $m\times(n-1)$ submatrices of H, denoted as $\bar{H}_1,\ldots,\bar{H}_q$, such that $\mathrm{rank}(\bar{H}_i) < \mathrm{rank}(H)$ ($i = 1,\ldots,q$), then there are at most q sources that can be extracted one by one via sequential blind extraction. Furthermore, the number of extractable sources is less than or equal to m.

Proof: See Appendix.

From Theorem 3, we have the following corollary.

$$B(z^{-1}) = \begin{bmatrix} 1 & & \\ -B_{21}(z^{-1}) & & \\ \vdots & \ddots & \\ -B_{m1}(z^{-1}) & & 1 \end{bmatrix} \begin{bmatrix} 1 & -B_{12}(z^{-1}) & \cdots & -B_{1m}(z^{-1}) \\ & 1 & & \\ & & \ddots & \\ & & & 1 \end{bmatrix}$$
$$= \begin{bmatrix} 1 & -B_{12}(z^{-1}) & \cdots & -B_{1m}(z^{-1}) \\ -B_{21}(z^{-1}) & 1 + B_{21}(z^{-1})B_{12}(z^{-1}) & \cdots & B_{21}(z^{-1})B_{1m}(z^{-1}) \\ \vdots & \vdots & \ddots & \vdots \\ -B_{m1}(z^{-1}) & B_{m1}(z^{-1})B_{12}(z^{-1}) & \cdots & 1 + B_{m1}(z^{-1})B_{1m}(z^{-1}) \end{bmatrix} \quad (5)$$

Corollary 1: If H is of full-column rank or nonsingular, then all sources can be extracted sequentially as their filtered versions.

Although only real-valued signals are considered in this section, all variables involved above can be complex-valued, and the extractability results can be applied directly in complex-valued signals.

III. Cost Function and Optimization Algorithm

In the preceding section, two blind extraction models and corresponding extractability analysis are presented. From the discussions, we can see that theoretically it is possible to extract true sources from ill-conditioned convolutive mixtures using the two extraction models. This section will introduce a cumulant-based cost function and the Gauss–Newton algorithm to extract filtered sources. For the extracted signals, we also propose another cost function for SISO systems to obtain the source.

We consider the case in which all entries of H are causal FIR filters only. From Theorem 1, we can choose a blind extraction filter bank B with all its entries being causal FIR filters.

Consider model (3) or its equivalent in the frequency domain (4). Suppose that $s_1, \ldots, s_n$ are n $(n \geq 2)$ non-Gaussian random sequences that are temporally and spatially independent. According to Theorem 1 in [12], for all k, l, if the output $y_1(k)$ is pairwise independent to $y_j(l)$, then $C_{jk_0}(z^{-1}) \equiv 0$ when there is a $C_{1k_0}(z^{-1}) \not\equiv 0, j = 2, \ldots, m$. That is, if there is a $c_{1k_0}(l_0) \neq 0$, then $c_{jk_0}(l) = 0$ for all l and $j = 2, \ldots, m$. Thus, the pairwise independence of one output with other $m-1$ outputs can be used as a blind extraction principle.

Following the idea in [33], [34], etc., next, we introduce a cost function based on cross cumulant as a criterion for blind source extraction, as shown in (8) at the bottom of the page, where ℓ is sufficiently large and represents the length of entries of C $(= BH)$, $k \geq \ell$.

Obviously, if $y_1(k)$ and $y_j(k-l)$ are pairwise independent for $l = 0, \ldots, \ell - 1, j = 2, \ldots, m$, then $J = 0$.

If complex-valued sources and channels are considered, then the following cost function based on fourth-order cumulant should be introduced as in [5], as shown in (9) at the bottom of the page, where y_i^* denotes a complex conjugate of y_i. Under the assumption that all sources are mutually independent sequences, $\bar{J}$ is a real-valued function with the real parts and imaginary parts of the extractor coefficients. Let ℓ_0 denote the number of all extractor coefficients, then $\bar{J}$ can be seen as a real-valued function of $2\ell_0$ real variables (real parts and imaginary parts of all extractor coefficients). Thus, the optimization procedure of $\bar{J}$ is similar to the real-valued case.

Based on the properties of cumulant, it is not difficult to prove the following result.

Theorem 4: Suppose that $s_1(t), \ldots, s_n(t)$ are sup-Gaussian (or sub-Gaussian) spatially independent random sequences with zero means. For the blind extraction model (3) or (4), if there is a filter bank b_{ij} $(i, j = 1, \ldots, m)$ with full rank z–transform matrix $B(z^{-1})$ such that $J = 0$ and $y_1 \not\equiv 0$, then y_1 is a filtered version of a single source, or new convolutive mixture of several inseparable sources; the other outputs of the model do not contain any component of y_1.

In many studies (e.g., [5], [24], and [26]) kurtosis-based criteria are used instead of cross-cumulant based criteria, as in (8). In [24], several contrast functions are obtained, of which their global maximum is the true solution under the assumption of invertible channels (full-column rank). However, if the systems are ill-conditioned, conditions F1 and F2 in [24] cannot be satisfied simultaneously, and there is no trivial matrix sequence $H(k)$ such that the equality of C2 holds. Thus it is very difficult to construct a kurtosis-based contrast for ill-conditioned systems. In [5], under the condition of invertible channels, several kurtosis-based criteria are established. It has been proved that all stable equilibria with respect to the composite impulse response result in true solutions (original sources), and those equilibria resulting in spurious solutions are unstable (saddle points). Furthermore, it also follows that all the stationary points of the criterion with respect to the equalizer coefficients are described by the stationary points of the criterion with respect to the composite impulse response. However, if the systems are ill-conditioned, this kind of one-to-one relationship between the two sets of stationary points does not exist: one set corresponds to the equalizer coefficients, the other set corresponds to the composite impulse response. In [26], if the channels are assumed to be invertible (sufficient-order case), a local extremum of the criterion implies a single source is extracted; otherwise, the local extremum only results in a new mixture of several sources, and the criterion is not a contrast of which the global extremum can not be ensured. Above all, if we use a kurtosis-based cost function, the global convergence of the corresponding algorithm cannot be ensured, and iteration may become stuck in a local extremum, which may result in a spurious solution. This can lead to the unfavorable position in which we cannot judge which extremum would result in a true solution. However, if we use the criterion in (8), though the global convergence of the corresponding algorithm also cannot be ensured, the true solution is the global minimum of the cost function $(J = 0)$ with local stability, and it is easy to judge whether or not we have obtained the true solution.

$$J = \sum_{l=0}^{\ell-1} \sum_{j=2}^{m} [\mathrm{Cum}_{2,2}^2(y_1(k), y_j(k-l)) + \mathrm{Cum}_{2,2}^2(y_j(k), y_1(k-l))] \tag{8}$$

$$\bar{J} = \sum_{l=0}^{\ell-1} \sum_{j=2}^{m} [\mathrm{Cum}^2(y_1(k), y_1^*(k), y_j(k-l), y_j^*(k-l)) + \mathrm{Cum}^2(y_j(k), y_j^*(k), y_1(k-l), y_1^*(k-l))] \tag{9}$$

Under the conditions in Theorem 4, blind extraction based on model (3) can be implemented by solving the following constrained minimization problem:

$$\min J \text{ subject to } \operatorname{rank}(B(z^{-1})) = m. \tag{10}$$

Since $B(z^{-1})$ in (5) is of full rank, blind source extraction based on model (6) can be carried out by solving the unconstrained minimization problem

$$\min J. \tag{11}$$

Define an $m^2\ell_1$ dimensional column vector

$$\tilde{b} = [b_{11}(0), \dots, b_{11}(\ell_1 - 1), \dots, b_{1m}(0), \dots, b_{1m}(\ell_1 - 1), \dots, b_{21}(0), \dots, b_{21}(\ell_1-1), \dots, b_{mm}(0), \dots, b_{mm}(\ell_1-1)]^T. \tag{12}$$

The following Gauss–Newton algorithm can be used to solve the optimization problems (10) and (11) for blind source extraction, as shown in (13) at the bottom of the page, where μ and β are positive constants, $\beta \le 1$, and I is the $m^2\ell_1 \times m^2\ell_1$ identity matrix.

As in [16], we can compute J and its partial derivatives with respect to variables $b_{ij}(k)$ using observable x_i $(i = 1, \dots, m)$. Note that every expectation involved the computation in (13) is approximated by a corresponding mean of a record of samples. In our experience, if the sources are independent sequences generated as in the example of this paper, the record length of 5000 is sufficient.

Once the iterative procedure for solving (10) is complete, it is important to check whether $|B(z^{-1})| \equiv 0$. If $|B(z^{-1})| \equiv 0$, or $y_1 = 0$ and $|B(z^{-1})| \not\equiv 0$, then one should choose another initial value of B and begin the iteration again.

If a filtered source is extracted, then we can use a deconvolution filter b_0 for deconvolution of the signal to obtain a signal source. Of course, if a new convolved mixture of several inseparable sources is extracted, then it is impossible to obtain a signal source using any deconvolution algorithm. In the following, we assume that y_1 is a filtered source, denote $u_1 = b_0 * y_1$. We will minimize the following cost function for deconvolution:

$$J_1 = \sum_{l=0}^{\ell_0-1} \operatorname{Cum}_{2,2}^2(u_1(k), u_1(k-l)) \tag{14}$$

where ℓ_0 is sufficiently large and $k \ge \ell_0$.

As a measure of extraction performance, we use the intersymbol interference (ISI_1) defined by

$$\mathrm{ISI}_1 = \frac{\sum_{i=1}^{n} \|c_{1i}\|^2 - \max_{1\le i\le n}\{\|c_{1i}\|^2\}}{\max_{1\le i\le n}\{\|c_{1i}\|^2\}} \tag{15}$$

where c_{1i} $(i = 1, \dots, n)$ are defined in (3). Obviously, $\mathrm{ISI}_1 = 0$ if and only if $C(z^{-1})$ has only one nonzero entry in the first row.

In the blind deconvolution, we use the following index ISI_2 as a measure of performance

$$\mathrm{ISI}_2 = \frac{\sum_{k=1}^{\ell_0} |\bar{c}(k)|^2 - \max_{1\le k\le \ell_0}\{|\bar{c}(k)|^2\}}{\max_{1\le k\le \ell_0}\{|\bar{c}_(k)|^2\}} \tag{16}$$

where $\bar{c} = b_0 * (c_{11} + \cdots + c_{1n})$. Obviously, $\mathrm{ISI}_2 = 0$ implies that $u_1 = b_0 * y_1$ is a single source up to a scale and a time delay.

IV. Simulation Results

In this section, we present a simulation example to illustrate the proposed algorithm.

Consider three sub-Gaussian sources $[s_1, s_2, s_3]^T$, where $s_1(t) = 3\sin(n_1(t) - 0.5)$, $s_2 = 2\cos(n_2(t)\pi)$, $s_3(t) = 3n_3(t) - 1.5$, n_1, n_2 and n_3 are independent uniform white noises with values in [0, 1]. The kurtosis values of s_1, s_2, s_3 are -0.5685, -6.1574, and -0.7067, respectively. The mixing filter bank is shown in (17) at the bottom of the page.

Now, we employ the proposed extraction approach to extract a single source. Clearly, the conditions in Theorem 1 are satisfied and a filtered signal of the source s_1 can be extracted.

Let the length of double-sided b_{ij} in (3) as 7 and the initial value of $B(z^{-1})$ as shown in the last equation at the bottom of the page. Note that if the performance index ISI_1 decreases

$$\tilde{b}(k+1) = \tilde{b}(k) - \left[\sum_{l=0}^{\ell-1}\sum_{j=2}^{m} 2\left(\frac{\partial \operatorname{Cum}_{2,2}(y_1(k), y_j(k-l))}{\partial \tilde{b}}\left[\frac{\partial \operatorname{Cum}_{2,2}(y_1(k), y_j(k-l))}{\partial \tilde{b}}\right]^T + \frac{\partial \operatorname{Cum}_{2,2}(y_j(n), y_1(k-l))}{\partial \tilde{b}}\left[\frac{\partial \operatorname{Cum}_{2,2}(y_j(k), y_1(k-l))}{\partial \tilde{b}}\right]^T\right) + \mu\beta^k I\right]^{-1} \frac{\partial J}{\partial \tilde{b}} \tag{13}$$

$$H(z^{-1}) = \begin{bmatrix} 1 + 0.5z^{-1} + 0.2z^{-2} & 0.3 + 0.4z^{-1} & 0.1 + 0.3z^{-1} \\ 0 & 0.3 + 0.61z^{-1} + 0.28z^{-2} & 0.1 + 0.47z^{-1} + 0.28z^{-2} \end{bmatrix} \tag{17}$$

$$\begin{bmatrix} 0.8 + 0.6z^{-1} + 0.2z^{-2} + 0.2z^{-3} & -0.7 + 0.3z^{-1} + 0.2z^{-2} + 0.2z^{-3} \\ 0.3 + 0.1z^{-1} + 0.2z^{-2} + 0.1z^{-3} & 0.8 + 0.2z^{-1} + 0.2z^{-2} + 0.1z^{-3} \end{bmatrix}$$

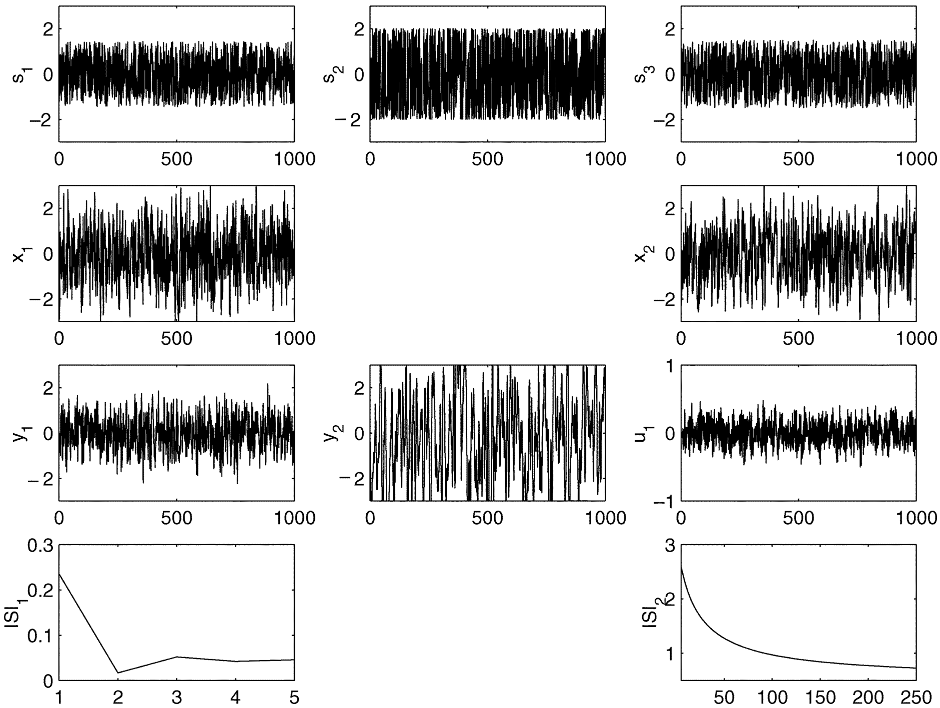


Fig. 1. Simulation results in the blind extraction and deconvolution.

fast and tends to zero during the iteration, then we think that the length and the initial value of $B(z^{-1})$ are set appropriately.

Using the algorithm (13), we can solve the optimization problem (10) and obtain the extraction filter bank $B(z^{-1})$. The three entries of the first row of $C(z^{-1}) = B(z^{-1})H(z^{-1})$ are shown in (18) at the bottom of the page.

Note that the maximum of the absolute values of coefficients of $c_{11}(z^{-1})$ is much greater than those of $c_{12}(z^{-1})$ and $c_{13}(z^{-1})$ in (18). (This is also shown in the subplot in the fourth row and first column of Fig. 1). We can see that y_1 can be taken as a convolutive signal from source s_1 only.

In the next step, blind deconvulution is performed to recover the source s_1. Let the length of deconvolution double-sided filter b_0 be 11, and the initial value of b_0 be $[0, -0.1, 0, -0.1, -0.2, 1, -0.2, -0.1, 0, -0.1, 0]$. Using the Gauss–Newton algorithm to minimize the cost function (14), we can obtain the deconvolution filter

$$b_0 = [0.0642, -0.0074, -0.0550, 0.1198, -0.0514, 0.2661, -0.1975, 0.0658, 0.0670, 0.0385, -0.0466].$$

Fig. 1 shows the simulation results. In the first row, the three subplots represent the three sources s_1, s_2, and s_3. The two subplots of the second row are the convolutive mixtures x_1 and x_2. In the third row, the first two subplots are the extracted signal y_1 and the remaining signal y_2, and the third subplot is deconvolved signal u_1. The two subplots of the fourth row show the iterative behaviors of ISI_1 and ISI_2. From (18) and Fig. 1, we can see that not only the filtered s_1 is extracted, but also s_1 is recovered nearly up to a scale and a time delay.

V. Concluding Remarks

Based on two blind extraction models, an extraction approach is presented for blind deconvolution of convolutive mixtures in ill-conditioned MIMO channels. Extractability is characterized with a necessary and sufficient condition. The sequential blind extraction approach can extract all potentially separable sources (at most equal to the number of sensors) from convolutive mixtures in ill-conditioned channels. The extraction is implemented by minimizing a cumulant-based cost function using the Gauss–Newton algorithm. A simulation example is given to illustrate the extraction approach.

Many avenues are open for further investigations. In view that all sources are assumed to be sup-Gaussian (or sub-Gaussian) for the cost function herein and the learning algorithm is an existing general-purpose optimization procedure, the remaining

$$\begin{cases} c_{11}(z^{-1}) = [0.0095z^4 - 0.0890z^3 - 0.1107z^2 + 0.5739z + 0.6564 + 0.2021z^{-1} \\ \quad -0.0223z^{-2} - 0.0418z^{-3} - 0.0086z^{-4}], \\ c_{12}(z^{-1}) = [0.0432z^4 + 0.0714z^3 + 0.0245z^2 - 0.0135z - 0.0462 - 0.0545z^{-1} \\ \quad -0.0589z^{-2} - 0.0140z^{-3} + 0.0111z^{-4}], \\ c_{13}(z^{-1}) = [0.0144z^4 + 0.0612z^3 + 0.0297z^2 + 0.0075z - 0.0973 - 0.0691z^{-1} \\ \quad -0.0376z^{-2} - 0.0153z^{-3} + 0.0111z^{-4}] \end{cases} \tag{18}$$

tasks include the development of more effective cost functions and more efficient algorithms.

APPENDIX

A. The Proof of Theorem 1

Necessity: If there is a full rank $m \times m$ matrix B such that the first row of $C = BH$ has nonzero entries $C_{1l_1}, \dots, C_{1l_p}$, and the l_ith column ($i = 1, \dots, p$) of C has only one nonzero entry C_{1l_i}. Without loss of generality, suppose that

$$BH = [B\hat{H}|B\overset{*}{H}] = \begin{bmatrix} c_1 & \cdots & c_p & 0 & \cdots & 0 \\ 0 & \cdots & 0 & c_{2(p+1)} & \cdots & c_{2n} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & \cdots & 0 & c_{m(p+1)} & \cdots & c_{mn} \end{bmatrix} \tag{19}$$

where

$$\hat{H} = \begin{bmatrix} H_{11} & \cdots & H_{1p} \\ \vdots & \ddots & \vdots \\ H_{m1} & \cdots & H_{mp} \end{bmatrix} \quad \overset{*}{H} = \begin{bmatrix} H_{1(p+1)}, & \dots, & H_{1n} \\ \vdots & \ddots & \vdots \\ H_{m(p+1)} & \cdots & H_{mn} \end{bmatrix}. \tag{20}$$

In view of (19) and full rank of B

$$\mathrm{rank}(\overset{*}{H}) = \mathrm{rank}(B\overset{*}{H}) < \mathrm{rank}(BH) = \mathrm{rank}(H) \tag{21}$$
$$\mathrm{rank}(\hat{H}) = \mathrm{rank}(B\hat{H}) = 1. \tag{22}$$

The necessity is obtained.

Sufficiency: Without loss of generality, suppose that H is of full row rank, that is, $\mathrm{rank}(H) = m$, and suppose that $\hat{H}$ and $\overset{*}{H}$ in (20) satisfy $\mathrm{rank}(\hat{H}) = 1$, $\mathrm{rank}(\overset{*}{H}) < \mathrm{rank}(H)$. In the following, we construct a full rank $m \times m$ matrix B such that the first row of $C = BH$ has nonzero entries $C_{11}, \dots, C_{1p}$, and the ith column ($i = 1, \dots, p$) of C has only one nonzero entry C_{1i} [see (19)].

From that $\mathrm{rank}(\hat{H}) = 1$, we have

$$\begin{aligned}[H_{11}, \dots, H_{m1}]^T &= g_2[H_{12}, \dots, H_{m2}]^T \\ &= \cdots = g_p[H_{1p}, \dots, H_{mp}]^T \end{aligned} \tag{23}$$

where $g_2, \dots, g_p \not\equiv 0$ are in $G(z^{-1})$.

Furthermore, since $\mathrm{rank}(\overset{*}{H}) < m$, the m rows of $\overset{*}{H}$ are linearly dependent. Therefore, there is a row vector of $\overset{*}{H}$ supposed to be $[H_{1(p+1)}, \dots, H_{1n}]$, such that

$$\begin{aligned}[H_{1(p+1)}, \dots, H_{1n}] = k_2[H_{2(p+1)}, \dots, H_{2n}] \\ + \cdots + k_m[H_{m(p+1)}, \dots, H_{mn}] \end{aligned} \tag{24}$$

where $k_2, \dots, k_m$ are functions in $G(z^{-1})$.

Since H is assumed to be of full row rank, we have

$$b_l = H_{1l} - \sum_{j=2}^{m} k_j H_{jl} \not\equiv 0, \; l = 1, \dots, p. \tag{25}$$

From (23), it is easy to obtain

$$b_1 = g_2 b_2 = \cdots = g_p b_p. \tag{26}$$

From (23) and (26), we have

$$\frac{H_{j1}}{b_1} = \cdots = \frac{H_{jp}}{b_p}, \qquad j = 1, \dots, m. \tag{27}$$

Set

$$B = \begin{bmatrix} 1 & -k_2 & \cdots & -k_m \\ -\frac{H_{21}}{b_1} & 1 + \frac{H_{21}}{b_1}k_2 & \cdots & \frac{H_{21}}{b_1}k_m \\ \vdots & \vdots & \ddots & \vdots \\ -\frac{H_{m1}}{b_1} & \frac{H_{m1}}{b_1}k_2 & \cdots & 1 + \frac{H_{m1}}{b_1}k_m \end{bmatrix} \tag{28}$$

from (27), then

$$BH = \begin{bmatrix} b_1 & \cdots & b_p & 0 & \cdots & 0 \\ 0 & \cdots & 0 & H_{2(p+1)} & \cdots & H_{2n} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & \cdots & 0 & H_{m(p+1)} & \cdots & H_{mn} \end{bmatrix}.$$

Thus, there exists a full rank blind extraction matrix B in (4) such that a convolutive mixture of p sources can be extracted. The sufficiency is obtained.

Multiplying the B in (28) by the least common denominator of its entries, we can take a new one to replace B with its each entry being an FIR filter. □

B. Proof of Theorem 3

Without loss of generality, assume that

$$\bar{H}_1 = \begin{bmatrix} H_{12} & \cdots & H_{1n} \\ \vdots & \ddots & \vdots \\ H_{m2} & \cdots & H_{mn} \end{bmatrix}, \dots,$$
$$\bar{H}_q = \begin{bmatrix} H_{12} & \cdots & H_{1(q-1)} & H_{1(q+1)} & \cdots & H_{1n)} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ H_{m2} & \cdots & H_{m(q-1)} & H_{m(q+1)} & \cdots & H_{mn} \end{bmatrix}.$$

Since $\mathrm{rank}(\bar{H}_1) < \mathrm{rank}(H)$, by Theorem 1, there is a nonsingular $m \times m$ matrix B_1 such that $B_1 H$ has the following form:

$$B_1 H = \begin{bmatrix} c_1 & 0 & \cdots & 0 \\ 0 & \tilde{H}_{22} & \cdots & \tilde{H}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \tilde{H}_{m2} & \cdots & \tilde{H}_{mn} \end{bmatrix}.$$

Obviously

$$B_1 \bar{H}_1 = \begin{bmatrix} 0 & \cdots & 0 \\ \tilde{H}_{22} & \cdots & \tilde{H}_{2n} \\ \vdots & \ddots & \vdots \\ \tilde{H}_{m2} & \cdots & \tilde{H}_{mn} \end{bmatrix}$$
$$B_1 \bar{H}_2 = \begin{bmatrix} c_1 & 0 & \cdots & 0 \\ 0 & \tilde{H}_{23} & \cdots & \tilde{H}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \tilde{H}_{m3} & \cdots & \tilde{H}_{mn} \end{bmatrix}. \tag{29}$$

Denote

$$\tilde{H}_1 = \begin{bmatrix} \tilde{H}_{22} & \cdots & \tilde{H}_{2n} \\ \vdots & \ddots & \vdots \\ \tilde{H}_{m2} & \cdots & \tilde{H}_{mn} \end{bmatrix} \quad \tilde{H}_2 = \begin{bmatrix} \tilde{H}_{23} & \cdots & \tilde{H}_{2n} \\ \vdots & \ddots & \vdots \\ \tilde{H}_{m3} & \cdots & \tilde{H}_{mn} \end{bmatrix}.$$

Since B_1 is of full rank, $\mathrm{rank}(B_1 H) = \mathrm{rank}(H)$. From (29)

$$\begin{aligned}\mathrm{rank}(H) &= \mathrm{rank}(B_1 H) = 1 + \mathrm{rank}(B_1 \bar{H}_1) \\ &= 1 + \mathrm{rank}(\tilde{H}_1) \\ \text{and } \mathrm{rank}(\bar{H}_2) &= \mathrm{rank}(B_1 \bar{H}_2) = 1 + \mathrm{rank}(\tilde{H}_2) \\ &< \mathrm{rank}(H) = 1 + \mathrm{rank}(\tilde{H}_1).\end{aligned}$$

Thus $\mathrm{rank}(\tilde{H}_2) < \mathrm{rank}(\tilde{H}_1)$.

By Theorem 1, there is a nonsingular $(m-1) \times (m-1)$ blind extraction matrix B_2 such that $B_2 \tilde{H}_1$ has a similar form as $B_1 H$.

By repeating the above process q times, we can obtain q nonsingular, blind extraction matrices $B_1, \ldots B_q$, with their dimensions being $m \times m, \ldots, (m-q+1) \times (m-q+1)$ respectively; they have similar characteristics as B_1 and B_2.

Let

$$\tilde{b} = \begin{bmatrix} I_q & \\ & B_q \end{bmatrix} \begin{bmatrix} I_{q-1} & \\ & B_{q-1} \end{bmatrix} \cdots \begin{bmatrix} I_2 & \\ & B_2 \end{bmatrix} B_1$$

then

$$\tilde{B} H = \begin{bmatrix} c_1 & & & \\ & \ddots & & \\ & & c_q & \\ & & & H_0 \end{bmatrix} \quad (30)$$

where I_i is an $(i-1) \times (i-1)$ identity matrix, $i = 2, \ldots, q$, and H_0 is an $(m-q) \times (m-q)$ matrix.

If there are $q+1$ sources that can be extracted sequentially, then H_0 in (30) satisfies the conditions in Theorem 1, and there are $q+1$ $m \times (n-1)$ submatrices of $\tilde{b}H$ with their ranks being $\mathrm{rank}(\tilde{b}H) - 1$. Since $\tilde{b}$ is nonsingular, H has $q+1$ $m \times (n-1)$–dimensional submatrices with their ranks being $\mathrm{rank}(H) - 1$, which contradicts the conditions of this theorem. Thus, there are at most q sources that can be extracted.

From this proof, we can see that the number of extractable sources is less than or equal to m.

□

REFERENCES

[1] A. Cichocki and S. Amari, *Adaptive Blind Signal and Image Processing: Learning Algorithms and Applications*. New York: Wiley, 2002.

[2] S. Amari and A. Cichocki, "Adaptive blind signal processing – Neural network approaches," *Proc. IEEE*, vol. 86, pp. 2026–2048, Oct. 1998.

[3] A. J. Bell and T. J. Sejnowski, "An information-maximization approach to blind separation and blind deconvolution," *Neural Comput.*, vol. 7, pp. 1129–1159, 1995.

[4] Y. Inouye and T. Sato, "Iterative algorithms based on multistage criteria for blind deconvolution," *IEEE Trans. Signal Processing*, vol. 47, pp. 1759–1764, June 1999.

[5] J. Tugnait, "Identification and deconvolution of multichannel linear non-Gaussian processes using higher order statistics and inverse filter criteria," *IEEE Trans. Signal Processing*, vol. 45, pp. 658–872, Mar. 1997.

[6] Y. Inouye and K. Tanebe, "Super-exponential algorithm for multichannel blind deconvolution," *IEEE Trans. Signal Processing*, vol. 48, pp. 881–888, Mar. 2000.

[7] J. Tugnait, "Blind spatio-temporal equalization and impulse response estimation for MIMO channels using a Godard cost function," *IEEE Trans. Signal Processing*, vol. 45, pp. 268–271, Jan. 1997.

[8] C. T. Ma, Z. Ding, and S. F. Yau, "A two-stage algorithm for MIMO blind deconvolution of nonstationary colored signals," *IEEE Trans. Signal Processing*, vol. 48, pp. 1187–1192, Apr. 2000.

[9] K. L. Yeung and S. F. Yau, "A cumulant-based super-exponential algorithm for blind deconvolution of multi-input multi-output systems," *Signal Processing*, vol. 67, pp. 141–162, 1998.

[10] S. Choi and A. Cichocki, "Cascade neural networks for multichannel blind deconvolution," *Electron. Lett.*, vol. 34, no. 12, pp. 1186–1187, 1998.

[11] R. Liu and G. Dong, "A foundamental theorem for multiple-channel blind equalization," *IEEE Trans. Circuits Syst. I*, vol. 44, pp. 472–473, May 1997.

[12] R. Liu and H. Luo, "Direct blind separation of independent non-Gaussian signals with dynamic channels," in *Proc. Int. Workshop Celluar Neural Networks Applications*, London, U.K., 1998, pp. 34–37.

[13] Y. Inouye and R. Liu, "A system-theoretic foundation for blind equalization of an FIR MIMO channel systems," in *Proc. IEEE Int. Symp. Circuits Systems*, vol. I, Geneva, Switzerland, 2000, pp. 120–123.

[14] L. Zhang, A. Cichocki, and S. Amari, "Geometrical structures of FIR manifold and their application to multi-channel blind deconvolution," *J. VLSI Signal Processing Syst.*, vol. 31, no. 1, pp. 31–44, 2002.

[15] L. Zhang, S. Amari, and A. Cichocki, "Semiparametric model and superefficiency in blind deconvolution," *Signal Processing*, vol. 81, no. 12, pp. 2535–2553, 2001.

[16] H. L. N. Thi and C. Jutten, "Blind source separation for convolutive mixtures," *Signal Processing*, vol. 45, pp. 209–229, 1995.

[17] S. I. Amari, A. Cichocki, and H. H. Yang, "Blind signal separation and extraction: Neural and information-theoretic approaches," in *Unsupervised Adaptive Filtering, Vol. I, Blind Source Separation*, S. Haykin, Ed. New York: Wiley-Interscience, 2000, ch. 3, pp. 88–93.

[18] K. Torkkola, "Blind separation of delayed and convolved sources," in *Unsupervised Adaptive Filtering, Vol. I, Blind Source Separation*, S. Haykin, Ed. New York: Wiley-Interscience, 2000, ch. 8, pp. 334–355.

[19] P. Comon, "Blind channel identification and extraction of more sources than sensors," in *Proc. SPIE* , 1998, pp. 2–13.

[20] A. Taleb, "An algorithm for the blind identification of N independent signals with two sensors," in *Proc. Int. Sysmp. Signal Processing Applications*, Kuala Lumpur, Malaysia, 2001, pp. 5–8.

[21] S. C. Douglas, "Blind signal separations and blind deconvolution," in *Handbook of Neural Network Signal Processing*, Y. H. Hu and J.-N. Hwang, Eds. Boca Raton, FL: CRC Press, 2001, pp. 7.1–7.31.

[22] L. Tong, "Identification of multichannel MA parameters using high-order statistics," *Signal Processing*, vol. 53, pp. 195–209, 1996.

[23] Y. Q. Li, A. Cichocki, and L. Q. Zhang, "Blind separation and extraction of binary sources," *IEICE Trans. Fund.*, vol. E86-A, no. 3, pp. 580–589, 2003.

[24] P. Comon, "Contrasts for multichannel blind deconvolution," *IEEE Signal Processing Lett.*, vol. 3, pp. 209–211, July 1996.

[25] P. Comon and L. Rota, "Blind separation of independent sources from convolutive mixtures," *IEICE Trans. Fund. Electron.*, vol. E86-A, no. 3, pp. 542–549, 2003.

[26] P. A. Regalia and M. Mboup, "Properties of some blind equalization criteria in noisy multiuser environments," *IEEE Trans. Singnal Processing*, vol. 49, no. 12, pp. 3112–3122, 2001.

[27] Y. Q. Li, J. Wang, and J. M. Zurada, "Blind extraction of singularly mixed source signals," *IEEE Trans. Neural Networks*, vol. 11, no. 6, pp. 1413–1422, 2000.

[28] H. L. N. Thi and C. Jutten, "Blind source separation for convolutive mixtures," *Signal Processing*, vol. 45, pp. 209–229, 1995.

[29] J. Tugnait, "Blind spatio-temporal equalization and impulse response estimation for MIMO channels using a Godard cost function," *IEEE Trans. Signal Processing*, vol. 45, pp. 268–271, Jan. 1997.

[30] ——, "Identification and deconvolution of multichannel linear non-Gaussian processes using higher order statistics and inverse filter criteria," *IEEE Trans. Signal Processing*, vol. 45, pp. 658–872, Mar. 1997.

[31] P. Loubaton and E. Moulines, "On blind multiuser forward link channel estimation by subspace method: Identifiability results," *IEEE Trans. Signal Processing*, vol. 48, pp. 2366–2376, Aug. 2000.

[32] A. Mansour and N. Ohnishi, "Multichannel blind separation of sources algorithm based on cross-cumulant and the Levenberg–Marquardt method," *IEEE Trans. Signal Processing*, vol. 47, pp. 3172–3175, Nov. 1999.

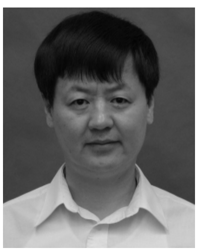
[33] A. Mansour and C. Jutten, "Fourth-order criteria for blind sources separation," *IEEE Trans. Signal Processing*, vol. 43, pp. 2022–2025, Aug. 1995.

[34] A. Mansour and N. Ohnishi, "Multichannel blind separation of sources algorithm based on cross-cumulant and the Levenberg–Marquardt method," *IEEE Trans. Signal Processing*, vol. 47, pp. 3172–3175, Nov. 1999.

[35] T. W. S. Chow and Y. Fang, "Neural blind deconvolution of MIMO noisy channels," *IEEE Trans. Circuits Syst. I*, vol. 48, pp. 116–120, Jan. 2001.

Yuanqing Li was born in Hunan Province, China, in 1966. He received the B.S. degree in applied mathematics from Wuhan University, Wuhan, China, in 1988, the M.S. degree in applied mathematics from South China Normal University, Guangzhou, China, in 1994, and the Ph.D. degree in control theory and applications from South China University of Technology, Guangzhou, China, in 1997.

Presently, he is a Researcher in the Laboratory for Advanced Brain Signal Processing, RIKEN Brain Science Institute, Saitama, Japan. He is also an Associate Professor at South China University of Technology. His research interests include automatic control, blind signal processing, neural networks, brain–computer interface, neural coding and neural decoding. He is the author or coauthor of more than 50 scientific papers in journals and conference proceedings.



Jun Wang (S'89–M'90–SM'93) received the B.S. degree in electrical engineering and an M.S. degree in systems engineering from Dalian University of Technology, Dalian, China, and the Ph.D. degree in systems engineering from Case Western Reserve University, Cleveland, OH, in 1982, 1985, and 1991, respectively.

He is a Professor of automation and computer-aided engineering at the Chinese University of Hong Kong. Prior to coming to Hong Kong in 1995, he was an associate professor at the University of North Dakota, Grand Forks. His current research interests include neural networks and their engineering applications.

He is an Associate Editor of the IEEE TRANSACTIONS ON NEURAL NETWORKS and IEEE TRANSACTIONS ON SYSTEMS, MAN, AND CYBERNETICS—B, and IEEE TRANSACTIONS ON SYSTEMS, MAN, AND CYBERNETICS—C.

Andrzej Cichocki was born in Poland. He received the M.Sc. (with honors), Ph.D., and Habilitate Doctorate (Doctor of Science) degrees, all in electrical engineering, from Warsaw University of Technology, Warsaw, Poland, in 1972, 1975, and 1982, respectively.

Since 1972, he has been with the Institute of Theory of Electrical Engineering, Measurements and Information Systems, Warsaw University of Technology, where he became a full Professor in 1991. He is the coauthor of three monographs: *MOS Switched-Capacitor and Continuous-Time Integrated Circuits and Systems* (New York: Springer-Verlag, 1989) with Prof. R. Unbehauen, *Neural Networks for Optimization and Signal Processing* (New York: Teubner-Wiley,1993/94) with Prof. R. Unbehauen, and *Adaptive Blind Signal and Image Processing* (New York: Wiley, 2003), with Prof. S. Amari. He is also author and coauthor of more than 150 research journal papers. He spent a few years at University Erlangen-Nuernberg (Germany) as Alexander Humboldt Research Fellow and Guest Professor. Since 1995, he has been working in the Frontier Research program and Brain Science Institute RIKEN, Saitama, Japan, as a Team Leader of the Laboratory for Open Information Systems and currently as a head of laboratory for Advanced Brain Signal Processing. His current research interests include biomedical signal and image processing, especially analysis and processing of multisensory, multimodal data, and human machine interface.

Dr. Cichocki is a member of the IEEE Signal Processing Society Technical Committee for Machine Learning for Signal Processing and IEEE Circuits and Systems Society Technical Committee on Blind Signal Processing.