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A super-exponential deflation method incorporated with higher-order correlations for blind deconvolution of MIMO linear systems☆

Kiyotaka Kohno[a,*], Yujiro Inouye[a,b], Mitsuru Kawamoto[c,d]

[a]Department of Electronic and Control Systems Engineering, Shimane University, 1060 Nishikawatsu, Matsue, Shimane 690-8504, Japan
[b]Laboratory for Advanced Brain Signal Processing, Brain Science Institute, RIKEN, 2-1, Hirosawa, Wako, Saitama 351-0198, Japan
[c]Information Technology Research Institute, National Institute of Advanced Science and Technology (AIST), Central 2, 1-1-1 Umezono, Tsukuba, Ibaraki 305-8568, Japan
[d]Bio-Mimetic Control Research Center, RIKEN, 2271-130, Anagahora, Shimoshidami, Moriyamaku, Nagoya 463-0003, Japan

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Abstract

The multichannel blind deconvolution of finite-impulse response (FIR) or infinite-impulse response (IIR) systems is investigated using the multichannel super-exponential deflation methods (MSEDMs). In the existing MSEDM, the so-called "second-order correlation method" is incorporated in order to estimate the contributions of an extracted source signal to the channel outputs. We propose a new MSEDM using higher-order correlations instead of second-order correlations to reduce the computational complexity in terms of multiplications and to accelerate the performance of deconvolution. Computer simulations show that the proposed method based on higher-order correlations is better than the existing method based on second-order correlations in the noiseless case or a noisy case.

Keywords: Blind signal processing; Blind deconvolution; Super-exponential deflation method; Higher-order correlations

1. Introduction

Multichannel blind deconvolution has recently received attention in such fields as digital communications, image processing, acoustic signal processing and neural information processing [1,2].

In 1993, Shalvi and Weinstein proposed an attractive approach to single-channel blind deconvolution called the *super-exponential methods* (SEMs) [3]. Extensions of their idea to multichannel deconvolution were presented by Inouye and Tanebe [4], Martone [5,6], and Yeung and Yau [7]. In particular, Inouye and Tanebe [4] proposed an multichannel super-exponential deflation method (MSEDM) using the second-order correlations. Moreover, Martone [6], and Kohno et al. [8,9] proposed MSEDMs using the higher-order correlations for MIMO (multiinput–multioutput) narrow-band channels (instantaneous mixtures). We extend

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*Corresponding author. Tel.: +81 859 24 5136; fax: +81 859 24 5009.
E-mail address: kohno@yonago-k.ac.jp (K. Kohno).

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their idea to the case of MIMO wide-band channels (convolutive mixtures).

In the present paper, we propose a new MSEDM using the higher-order correlations for MIMO wide-band channels, and show the effectiveness of the proposed method by computer simulations.

The present paper uses the following notation: Let Z denote the set of all integers. Let $\boldsymbol{C}^{m\times n}$ denote the set of all $m\times n$ matrices with complex components. The superscripts $\mathrm{T}, *, \mathrm{H}$ and $\dagger$ denote, respectively, the transpose, the complex conjugate, the complex conjugate transpose (Hermitian) and the (Moore–Penrose) pseudoinverse operations of a matrix. Let $i=\overline{1,n}$ stand for $i=1,2,\ldots,n$.

2. Assumptions and preliminaries

We consider an MIMO wide-band channel with n inputs and m outputs as described by

$$\boldsymbol{y}(t)=\sum_{k=-\infty}^{\infty}\boldsymbol{H}^{(k)}\boldsymbol{s}(t-k)+\boldsymbol{n}(t),\quad t\in Z, \tag{1}$$

where $\boldsymbol{s}(t)$ is an n-column vector of input (or source) signals, $\boldsymbol{y}(t)$ is an m-column vector of channel outputs, $\boldsymbol{n}(t)$ is an m-column vector of Gaussian noises, and $\{\boldsymbol{H}^{(k)}\}$ is an $m\times n$ impulse response matrix sequence.

The transfer function of the channel is defined by

$$\boldsymbol{H}(z)=\sum_{k=-\infty}^{\infty}\boldsymbol{H}^{(k)}z^{k},\quad z\in C. \tag{2}$$

To recover the source signals, we process the output signals by an $n\times m$ deconvolver $\boldsymbol{W}(z)$ described by

$$\boldsymbol{z}(t)=\sum_{k=-\infty}^{\infty}\boldsymbol{W}^{(k)}\boldsymbol{y}(t-k),\quad t\in Z. \tag{3}$$

The objective of multichannel blind deconvolution is to construct a deconvolver $\boldsymbol{W}(z)$ that recovers the original source signals only from the measurements of the corresponding outputs. For the time being, it is assumed for theoretical analysis that the noise term $\boldsymbol{n}(t)$ in (1) is absent. However, all the signals and the parameters of the systems are allowed to be complex-valued.

We put the following assumptions on the systems and the source signals.

(A1) The transfer function $\boldsymbol{H}(z)$ is stable and has full column rank on the unit circle $|z|=1$ (this implies that the unknown system has less inputs than outputs, i.e., $n\leqslant m$, and there exists a left stable inverse of the unknown system).

(A2) The input sequence $\{\boldsymbol{s}(t)\}$ is a complex, zero-mean, non-Gaussian random vector process with element processes $\{s_i(t)\}$, $i=\overline{1,n}$ being mutually independent. Moreover, each element process $\{s_i(t)\}$ is an i.i.d. process with a nonzero variance σ_i^2 and a nonzero fourth-order cumulant γ_i. The variances σ_i^2's and the fourth-order cumulants γ_i's are unknown.

(A3) The deconvolver $\boldsymbol{W}(z)$ is an finite-impulse response (FIR) system of sufficient length L so that the truncation effect can be ignored.

Based on assumption A3, let us consider an FIR deconvolver with the transfer function $\boldsymbol{W}(z)$ given by

$$\boldsymbol{W}(z)=\sum_{k=L_1}^{L_2}\boldsymbol{W}^{(k)}z^{k}, \tag{4}$$

where L_1 and L_2 are, respectively, the first and last superscripted numbers of the tap coefficients $\boldsymbol{W}^{(k)}$'s of the deconvolver $\boldsymbol{W}(z)$, and the length $L{:=}L_2-L_1+1$ is taken to be sufficiently large. Let $\tilde{\boldsymbol{w}}_i$ be the mL-column vector consisting of the tap coefficients (corresponding to the ith output) of the deconvolver defined by

$$\tilde{\boldsymbol{w}}_i{:=}[\boldsymbol{w}_{i,1}^{\mathrm{T}},\boldsymbol{w}_{i,2}^{\mathrm{T}},\ldots,\boldsymbol{w}_{i,m}^{\mathrm{T}}]^{\mathrm{T}}\in\boldsymbol{C}^{mL}, \tag{5}$$

$$\boldsymbol{w}_{i,j}=[w_{i,j}^{(L_1)},w_{i,j}^{(L_1+1)},\ldots,w_{i,j}^{(L_2)}]^{\mathrm{T}}\in\boldsymbol{C}^{L}, \tag{6}$$

where $w_{i,j}^{(k)}$ is the (i,j)th element of matrix $\boldsymbol{W}^{(k)}$.

Inouye and Tanebe [4] proposed an *multichannel super-exponential algorithm* (MSEA) for finding the tap coefficient vectors $\tilde{\boldsymbol{w}}_i$'s of the deconvolver $\boldsymbol{W}(z)$, of which each iteration consists of the following two steps:

$$\tilde{\boldsymbol{w}}_i^{[1]}=\tilde{\boldsymbol{R}}_L^{\dagger}\tilde{\boldsymbol{d}}_i\quad\text{for } i=\overline{1,n}, \tag{7}$$

$$\tilde{\boldsymbol{w}}_i^{[2]}=\frac{\tilde{\boldsymbol{w}}_i^{[1]}}{\sqrt{\tilde{\boldsymbol{w}}_i^{[1]H}\tilde{\boldsymbol{R}}_L\tilde{\boldsymbol{w}}_i^{[1]}}}\quad\text{for } i=\overline{1,n}, \tag{8}$$

where $(\cdot)^{[1]}$ and $(\cdot)^{[2]}$ stand, respectively, for the result of the first step and the result of the second step. Let $\tilde{\boldsymbol{y}}(t)$ be the mL-column vector consisting of the L consecutive inputs of the deconvolver defined by

$$\tilde{\boldsymbol{y}}(t){:=}[\bar{\boldsymbol{y}}_1(t)^{\mathrm{T}},\bar{\boldsymbol{y}}_2(t)^{\mathrm{T}},\ldots,\bar{\boldsymbol{y}}_m(t)^{\mathrm{T}}]^{\mathrm{T}}\in\boldsymbol{C}^{mL}, \tag{9}$$

$$\bar{\boldsymbol{y}}_i(t){:=}[y_i(t-L_1),y_i(t-L_1-1),\ldots,y_i(t-L_2)]^{\mathrm{T}}\in\boldsymbol{C}^{L}, \tag{10}$$

where $y_i(t)$ is the ith element of the output vector $\boldsymbol{y}(t)$ of the channel in (1). Then the correlation matrix $\tilde{R}_L$

(defined by (41) and (42) in [4]) is represented as

$$\tilde{\boldsymbol{R}}_L = E[\tilde{\boldsymbol{y}}^*(t)\tilde{\boldsymbol{y}}^{\mathrm{T}}(t)] \in \boldsymbol{C}^{mL\times mL}, \tag{11}$$

and the fourth-order cumulant vector $\tilde{\boldsymbol{d}}_i$ is defined by

$$\tilde{\boldsymbol{d}}_i := [\boldsymbol{d}_{i,1}^{\mathrm{T}}, \boldsymbol{d}_{i,2}^{\mathrm{T}}, \ldots, \boldsymbol{d}_{i,m}^{\mathrm{T}}]^{\mathrm{T}} \in \boldsymbol{C}^{mL}, \tag{12}$$

whose jth block element $\boldsymbol{d}_{i,j}$ is the L-column vector with rth element $[d_{i,j}]_r$ defined by

$$[d_{i,j}]_r = \mathrm{cum}(z_i(t), z_i(t), z_i^*(t), y_j^*(t-r)) \quad \text{for } r = 0, \pm 1, \pm 2, \ldots, \tag{13}$$

and $\tilde{\boldsymbol{d}}_i$ is represented as

$$\begin{aligned}\tilde{\boldsymbol{d}}_i = {} & E[|z_i(t)|^2 z_i(t)\tilde{\boldsymbol{y}}^*(t)] \\ & - 2E[|z_i(t)|^2]E[z_i(t)\tilde{\boldsymbol{y}}^*(t)] \\ & - E[z_i^2(t)]E[z_i^*(t)\tilde{\boldsymbol{y}}^*(t)] \in \boldsymbol{C}^{mL},\end{aligned} \tag{14}$$

where $E[x]$ denotes the expectation of a random variable x. We note that the last term can be ignored in case of $E[s_i^2(t)] = 0$ for all $i = \overline{1,n}$, in which case $E[z_i^2(t)] = 0$ for all $i = \overline{1,n}$.

3. A super-exponential deflation method incorporated with higher-order correlations

The *multichannel super-exponential deflation method* (MSEDM) proposed by Inouye and Tanebe [4] uses the second-order correlations to estimate the contributions of an extracted source signal to the channel outputs. In this section, we utilize higher-order correlations instead of the second-order correlations in order to estimate the contributions of an extracted source signal to the channel outputs. For notational simplicity, we confine ourselves to fourth-order correlations although our results are expandable to higher-order correlations.

Now, let us introduce n mL-column vectors as intermediate tap coefficients vectors of the deconvolver defined as

$$\tilde{\boldsymbol{c}}_i := [\boldsymbol{c}_{i,1}^{\mathrm{T}}, \boldsymbol{c}_{i,2}^{\mathrm{T}}, \ldots, \boldsymbol{c}_{i,m}^{\mathrm{T}}]^{\mathrm{T}} \quad \text{for } i = \overline{1,n}, \tag{15}$$

$$\boldsymbol{c}_{i,j} := [c_{i,j}^{(L_1)}, c_{i,j}^{(L_1+1)}, \ldots, c_{i,j}^{(L_2)}]^{\mathrm{T}}. \tag{16}$$

Then, the proposed algorithm is summarized as follows.

Step 1: Set $i = 1$ (where i denotes the order of an input extracted).

Step 2: Carry out the following iterations enough to extract an input after $\tilde{\boldsymbol{c}}_i$ was initialized by its appropriate value. Each of the iterations consists of the two steps as follows:

$$\tilde{\boldsymbol{c}}_i^{[1]} = \tilde{\boldsymbol{R}}_L^{\dagger}\tilde{\boldsymbol{d}}_i, \tag{17}$$

$$\tilde{\boldsymbol{c}}_i^{[2]} = \frac{\tilde{\boldsymbol{c}}_i^{[1]}}{\sqrt{\tilde{\boldsymbol{c}}_i^{[1]H}\tilde{\boldsymbol{R}}_L\tilde{\boldsymbol{c}}_i^{[1]}}}, \tag{18}$$

where $\tilde{\boldsymbol{R}}_L$ and $\tilde{\boldsymbol{d}}_i$ are, respectively, calculated by (11) and (14) using the values of the outputs $y_k(t)$'s ($k = \overline{1,m}$) and the values of the deconvolver outputs $z_i(t)$'s with $w_{i,j}^{(k)}$'s replaced by the corresponding values of $c_{i,j}^{(k)}$'s obtained before the iteration.

Step 3: As a possibly scaled and time-shifted estimate of an input $s_{j_i}(t)$, calculate the deconvolver output $z_i(t)$ by

$$z_i(t) = \sum_{j=1}^{m}\sum_{k=-\infty}^{\infty} c_{i,j}(k)y_j(t-k), \tag{19}$$

where $c_{i,j}(k)$'s are the new values obtained at Step 2. Then, calculate the fourth-order cross-correlations of the deconvolver outputs $z_i(t)$'s with the channel outputs $y_k(t)$'s, and define a possibly scaled and time-shifted estimate of the channel element $\hat{h}_{k,j_i}(\tau)$ as

$$\hat{h}_{k,j_i}(\tau) := \mathrm{cum}(z_i^*(t-\tau), z_i^*(t-\tau), z_i(t-\tau), y_k(t)). \tag{20}$$

Then, consider the reconstructed contribution of $z_i(t)$ to the channel output $y_k(t)$'s defined by

$$\hat{y}_{k,j_i}(t) := \frac{\sigma_{j_i}^4}{\gamma_{j_i}}\sum_{\tau=-\infty}^{\infty}\hat{h}_{k,j_i}(\tau)z_i(t-\tau), \tag{21}$$

where $\sigma_{j_i}^2/\gamma_{j_i}$ is introduced to adjust the difference between the scale of the contribution of $z_i(t)$ and the scale of the contribution of source $s_{j_i}(t)$ to the channel output $y_k(t)$.

Step 4: Remove the above contributions from the outputs $y_k(t)$'s to define the outputs of a linear system with m outputs and $n-1$ inputs. These are given by

$$y_k^{(i)}(t) := y_k(t) - \hat{y}_{k,j_i}(t), \quad k = \overline{1,m}. \tag{22}$$

Step 5: If $i < n$, then set $i = i + 1$ and $y_k(t) = y_k^{(i)}(t)$ for $k = \overline{1,m}$ and go back to Step 2. If $i = n$, then stop here.

As an important remark on Step 2 in the above algorithm, in the conventional MSEDM [4], the second-order cross-correlations of $z_i(t)$'s with the channel outputs $y_k(t)$'s are used and $\hat{h}_{k,j_i}(\tau)$ is defined as

$$\hat{h}_{k,j_i}(\tau) := E[y_k(t)z_i^*(t-\tau)] \quad \text{for } k = \overline{1,m}. \tag{23}$$

In implementing above the algorithm, all the expectations in (11) and (14) are replaced with their samples averages over appropriate data records.

For the details of the derivation for calculating the tap coefficients of the overall deconvolver $\boldsymbol{W}(z)$ from the intermediate deconvolver $\boldsymbol{C}(z)$, see Eqs. (60) and (61) in [4].

Let us analyze the above method. After the first cycle of the iteration, the first deconvolver output $z_1(t)$ is a possibly scaled and time-shifted version of one of the channel input, that is,

$$z_1(t) = \rho s_{j_1}(t-k_1), \quad j_1 \in \{1,2,\ldots,n\}, \tag{24}$$

where $|\rho| = 1/\sigma_{j_1}$ and k_1 represents a delay-time, which may belong to the interval $[K+L_1, L_2]$ (see (36) for the derivation of the above relation), i.e.,

$$k_1 \in [K+L_1, L_2], \tag{25}$$

in the case when the channel $\boldsymbol{H}$ is an FIR system with $\{\boldsymbol{H}^{(k)}\}_0^{K-1}$, and the deconvolver $\boldsymbol{W}$ is an FIR system with $\{\boldsymbol{W}^{(k)}\}_{k=L_1}^{L_2}$. Since

$$\begin{aligned}&\mathrm{cum}(z_i^*(t-\tau), z_i^*(t-\tau), z_i(t-\tau), y_k(t))\\&\quad = \mathrm{cum}(z_i^*(t), z_i^*(t), z_i(t), y_k(t+\tau)),\end{aligned} \tag{26}$$

it follows from (20) (with $i=1$) and (24)

$$\begin{aligned}\hat{h}_{k,j_1}(\tau) &= \mathrm{cum}(z_1^*(t), z_1^*(t), z_1(t), y_k(t+\tau))\\
&= \sum_{j=1}^{n}\sum_{l=-\infty}^{\infty} h_{k,j}(l)\,\mathrm{cum}(z_1^*(t), z_1^*(t), z_1(t),\\
&\qquad s_j(t+\tau-l))\\
&= \rho^{*2}\rho \sum_{j=1}^{n}\sum_{l=-\infty}^{\infty} h_{k,j}(l)\,\mathrm{cum}(s_{j_1}^*(t-k_1),\\
&\qquad s_{j_1}^*(t-k_1), s_{j_1}(t-k_1), s_j(t+\tau-l))\\
&= \rho^{*2}\rho h_{k,j_1}(k_1+\tau)\gamma_{j_1},\end{aligned} \tag{27}$$

which means

$$\hat{h}_{k,j_1}(\tau) = |\rho|^2\rho^*\gamma_{j_1} h_{k,j_1}(k_1+\tau). \tag{28}$$

Substituting (24) and (28) into (21) (with $i=1$) gives

$$\begin{aligned}\hat{y}_{k,j_1}(t) &= \frac{\sigma_{j_1}^4}{\gamma_{j_1}}\sum_{\tau=-\infty}^{\infty} |\rho|^4\gamma_{j_1} h_{k,j_1}(k_1+\tau) s_{j_1}(t-\tau-k_1)\\
&= \sum_{\tau=-\infty}^{\infty} h_{k,j_1}(k_1+\tau) s_{j_1}(t-\tau-k_1)\\
&= \sum_{\tau=-\infty}^{\infty} h_{k,j_1}(\tau) s_{j_1}(t-\tau).\end{aligned} \tag{29}$$

Thus, we obtain from (22)

$$\begin{aligned}y_k^{(1)}(t) &= y_k(t) - \hat{y}_{k,j_1}(t)\\
&= \sum_{j=1}^{n}\sum_{\tau=-\infty}^{\infty} h_{k,j}(\tau)s_j(t-\tau) - \sum_{\tau=-\infty}^{\infty} h_{k,j_1}(\tau)s_{j_1}(t-\tau)\\
&= \sum_{j=1, j\neq j_1}^{n}\sum_{\tau=-\infty}^{\infty} h_{k,j}(\tau)s_j(t-\tau),\end{aligned} \tag{30}$$

which shows that $y_k^{(1)}(t)$ does not contain the contribution of the source $s_{j_1}(t)$.

As one of the advantages of the above method, we can reduce the computational loads for calculating (20) and (21) as follows: Using the definitions of $\hat{h}_{k,j_i}$ and $[d_{i,j}]_\tau$ (see (20) and (13)), we have

$$\hat{h}_{k,j_i}(\tau) = [d_{i,k}]_{-\tau}^*. \tag{31}$$

Therefore, (21) becomes

$$\begin{aligned}\hat{y}_{k,j_i}(t) &= \frac{\sigma_{j_i}^4}{\gamma_{j_i}}\sum_{\tau=-\infty}^{\infty} \hat{h}_{k,j_i}(\tau) z_i(t-\tau)\\
&= \frac{\sigma_{j_i}^4}{\gamma_{j_i}}\sum_{\tau=L_1}^{L_2} [d_{i,k}]_\tau^* z_i(t+\tau),\end{aligned} \tag{32}$$

where the coefficients $[d_{i,k}]_\tau$'s are available at the first step (17) of the two-step iteration (17) and (18). This is a *novel key point* of our proposed method.

Some remarks are given below on conditions for the indices L_1 and L_2 of the deconvolver. In the following discussion, we assume that delay-time k_1 in (24) is known or estimated ahead. It follows from (28) and (31) that

$$h_{k,j_1}(\tau+k_1) = \frac{1}{\alpha}\hat{h}_{k,j_1}(\tau) = \frac{1}{\alpha}[d_{i,j}]_{-\tau}^*, \tag{33}$$

where $\alpha = |\rho^2|\rho^*\gamma_{j_1}$. When the channel $\boldsymbol{H}$ is an FIR system with $\{\boldsymbol{H}^{(k)}\}_0^{K-1}$ and the deconvolver $\boldsymbol{W}$ is an FIR system with $\{\boldsymbol{W}^{(k)}\}_{k=L_1}^{L_2}$, the support of the function $h_{k,j_1}(\tau)$ is the interval $[0,K]$ and the support of the function $[d_{i,k}]_\tau$ is the interval $[L_1, L_2]$. Here, given a function $h(\tau)$ defined on Z, the subset $\{\tau \in Z : h(\tau)\neq 0\}$ is called the *support* of the function h. Therefore, in order for the sequence $[d_{i,k}]_{-\tau}^*$ to determine the values of the sequence $h_{k,j_1}(\tau+k_1)$ based on (33), the support of $h_{k,j_1}(\tau+k_1)$ should be included in the support of $[d_{i,k}]_{-\tau}^*$, that is,

$$[-k_1, -k_1+K] \subset [-L_2, -L_1], \tag{34}$$

which implies

$$L_1 \leqslant k_1 - K, \quad L_2 \geqslant k_1, \tag{35}$$

or

$$k_1 \in [L_1+K, L_2]. \tag{36}$$

Thus the first tap index L_1 and the last tap index L_2 of the deconvolver are chosen to satisfy the conditions

$$L_1 \leqslant k_1 - K, \tag{37}$$

$$L_2 \geqslant k_1. \tag{38}$$

4. Simulations

To demonstrate the effectiveness of proposed method, some computer simulations were conducted. We considered an MIMO channel $\boldsymbol{H}(z)$ with two inputs and three outputs which is defined below by (39). $\boldsymbol{H}(z)$ was assumed that its length is three ($K = 3$).

$$\boldsymbol{H}(z) = \sum_{k=0}^{2} \boldsymbol{H}^{(k)} z^k = \begin{bmatrix} 1.00 + 0.15z + 0.10z^2 & 0.65 + 0.25z + 0.15z^2 \\ 0.50 - 0.10z + 0.20z^2 & 1.00 + 0.25z + 0.10z^2 \\ 0.60 + 0.10z + 0.40z^2 & 0.10 + 0.20z + 0.10z^2 \end{bmatrix}. \tag{39}$$

The length of the deconvolver was chosen to be six ($L = 6$) for $\boldsymbol{H}(z)$ [13,14]. We set the values of tap coefficients of $\boldsymbol{c}_1(z)$ to be zero except for $c_{11}^{(3)} = 1$ in case of $i = 1$, and those of $\boldsymbol{c}_2(z)$ to be zero except for $c_{22}^{(3)} = 1$ in case of $i = 2$. Two source signals were chosen to be 4-PSK and 8-PSK signals, respectively (see Fig. 2(a) and (b)). Three independent Gaussian noises (with identical variance σ_w^2) were added to the three outputs $y_i(t)$'s at various SNR levels. The SNR is defined as SNR:=$10\log_{10}(\sigma_i^2/\sigma_w^2)$, where σ_i^2's are the variances of $s_i(t)$'s and are equal to one. As a measure of performance, we use the MIMO intersymbol interference (M_{ISI}) [8].

First we considered the noiseless case, i.e., the case at SNR $= \infty$ dB. Table 1 shows the averages of the performance results over 10 independent Monte Carlo runs for the two methods, the proposed method and the existing MSEDM incorporated with second-order correlations [4] in this case. In each Monte Carlo run, $\tilde{\boldsymbol{R}}_L$ was estimated using 20,000 data samples and we set the number of iterations of (17) and (18) in Step 2 to be eight. In each iteration of two steps (17) and (18), $\tilde{\boldsymbol{d}}_i$ was also estimated using 20,000 data samples. It can be seen from Table 1 that our proposed method is superior to the existing MSEDM in performance by about 1 dB when the second source signal is recovered. Fig. 1 shows the signal constellations for the proposed method in this case. It can be seen from Fig. 1 that two source signals are recovered.

Table 1
Comparison of the performances of the two methods in the noiseless case

Method	M_{ISI} (dB)
The existing MSEDM	−18.67
The proposed method	−20.00

Secondly we considered noisy cases, i.e., the cases at SNR = 0, 5, 10, 15, 20 and ∞ dB, respectively. Fig. 2 shows the averages of the performance results over the 10 independent Monte Carlo runs in these cases. It can be seen from Fig. 2 that the proposed method is superior in performance to the existing MSEDM even if the power of additive noise increases.

The most important advantage of the proposed method is that there is no necessity of the calculations of the higher-order cross-correlations $\hat{h}_{k,j_i}(\tau)$ shown in (20). In the existing MSEDM, the second-order cross-correlations $\hat{h}_{k,j_i}(\tau)$ should be calculated by (23). Therefore, we can reduce the computational loads for calculating $\hat{h}_{k,j_i}(\tau)$. This is illustrated numerically below.

Table 2 shows the averages of the numbers of floating point operations (flops) per a Monte Carlo run over 10 independent Monte Carlo runs obtained by using the built-in function "flops" in MTLAB Version 5.2. Table 3 shows the averages of execution times per a Monte Carlo run over 10 independent Monte Carlo runs on a PC with an 3.2 GHz processor and 1 GB main memories used for simulations. In each Monte Carlo run, we set the number of iterations of (17) and (18) to be one.

It can be seen from Tables 2 and 3 that the number of floating point operations and the execution times for the proposed method are better than the existing MSEDM at about 1.6% and 7%, respectively. Besides, we consider that one of reasons why the proposed method is superior to the existing MSEDM in performance by about 1 dB for the noiseless case is that the computational errors corresponding to the methods might decrease as their computational loads decrease.

Thirdly we compared the proposed method in performance with another method, the eigenvector algorithm (EVA) [10–12] using the same deflation

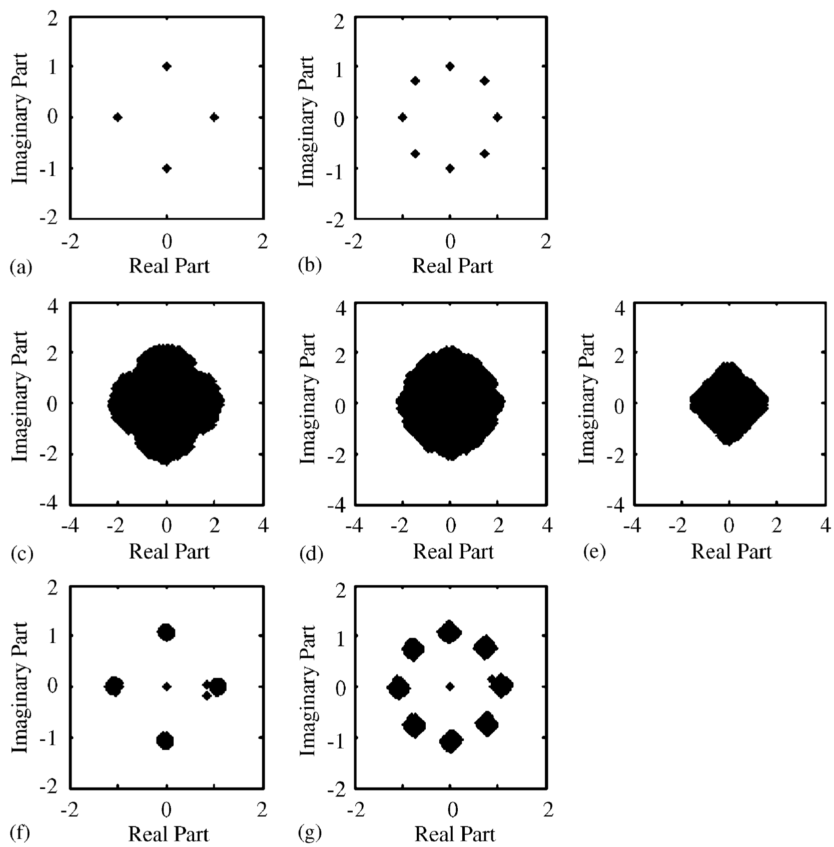

Fig. 1. Signal constellations of channel inputs (a) $s_1(t)$, (b) $s_2(t)$, channel outputs (c) $y_1(t)$, (d) $y_2(t)$, (e) $y_3(t)$, and deconvolver outputs (f) $z_1(t)$, (g) $z_2(t)$.

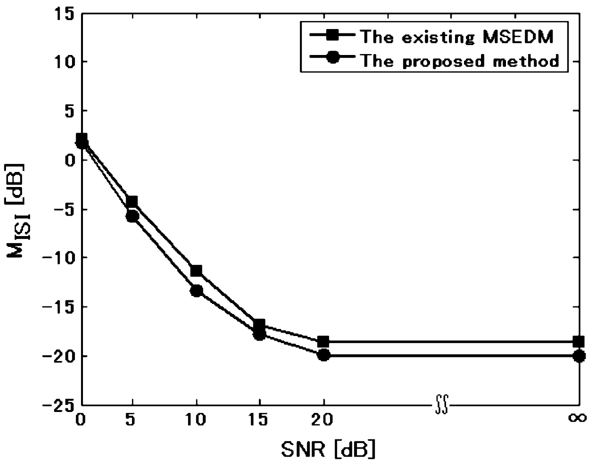

Fig. 2. Comparison of the performances of the two methods in the noisy cases.

Table 2
Comparison of the numbers of floating point operations of the two methods in the noiseless case

Method	The number of flops
The existing MSEDM	3.0834×10^8
The proposed method	3.0340×10^8

Table 3
Comparison of the execution times of the two methods in the noiseless case

Method	Execution time (s)
The existing MSEDM	49.38
The proposed method	45.88

method in [4] for the extraction of all the sources. Fig. 3 shows the average of the performance results over 10 Monte Carlo runs for the proposed method and the EVA in the six cases, the same cases as Fig. 2. Tables 4 and 5 show the average of the numbers of floating point operations (flops) and the average of execution times per a Monte Carlo run over 10 independent Monte Carlo runs.

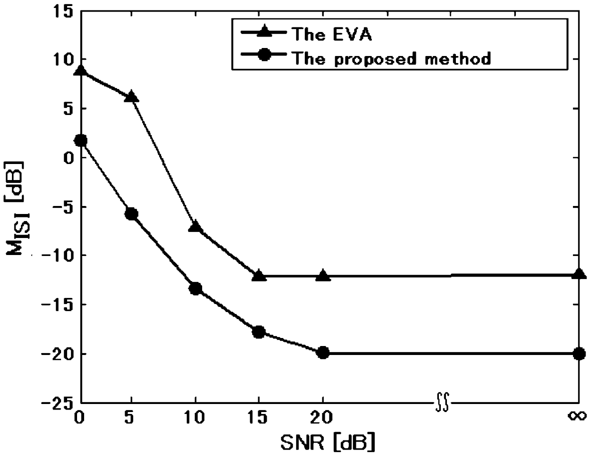

Fig. 3. Comparison of the performances of the proposed method and the EVA in the noisy cases.

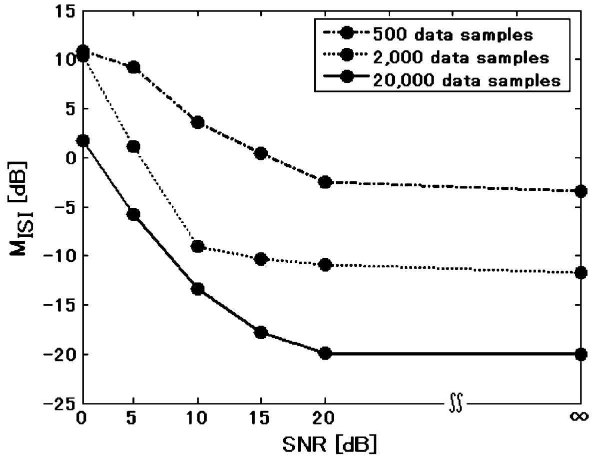

Fig. 4. Comparison of the performances of the proposed method by changing the number of data samples in the noisy cases.

Table 4
Comparison of the numbers of floating point operations of the proposed method and the EVA in the noiseless case

Method	The number of flops
The EVA	10.5273×10^8
The proposed method	3.0340×10^8

Table 5
Comparison of the execution times of the proposed method and the EVA in the noiseless case

Method	Execution time (s)
The EVA	61.12
The proposed method	45.88

It can be seen from Fig. 3 that the proposed method is superior in performance to the EVA by about 8 dB for the noiseless case and even if the power of additive noise increases. Besides, it can be seen from Tables 4 and 5 that the number of floating point operations and the execution times for the proposed method are better than the EVA at about 71% and 25%, respectively. According to these results, we conclude that the proposed super-exponential algorithm is effective more than the eigenvector algorithm using the deflation method.

We investigated the performance of the proposed method by changing the number of data samples. Fig. 4 shows the averages of the performance results of the proposed method (over 10 independent Monte Carlo runs) using 20,000, 2000 and 500 data samples, respectively. It can be seen from Fig. 4 that the accuracy of performance increases as the number of data samples increases.

5. Conclusions

We have proposed a new multichannel super-exponential deflation method using higher-order correlations instead of second-order correlations for estimating the contributions of an extracted source signal to the channel outputs in order to reduce the computational complexity and to accelerate the performance of deconvolution. By computer simulations, it has been shown that the method incorporated with fourth-order correlations is superior in performance to the two methods, the existing MSEDM incorporated with second-order correlations and the EVA, in the noiseless case and noisy cases.

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