Eigenvector Algorithms with Reference Signals for Frequency Domain BSS

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Abstract. This paper describes blind source separation (BSS) problems in the frequency domain using an eigenvector algorithm (EVA) with reference signals. The proposed EVA has such an attractive feature that all source signals are separated simultaneously from their mixtures. This is an advantage against the methods using deflation process (e.g., super-exponential method), because those methods sometimes do not work so as to converge to desired solutions, due to deflation failure. Computer simulation demonstrates the validity of the proposed EVA.

1 Introduction

This paper deals with the blind source separation (BSS) problem for a multiple-input multiple-output (MIMO) static system driven by independent source signals. To solve this problem, we draw on the ideas of eigenvector algorithms (EVAs) with reference signals. Jelonnek et al. have proposed EVAs derived from a criterion using a reference signal, in order to solve blind equalization of single-input single-output (SISO) systems [1,2]. They have shown that the equalizer can be derived from the eigenvectors of a fourth-order cumulant matrix. In this paper, the EVA derived from a criterion with reference signals is used for solving the BSS problem of MIMO static systems. The proposed EVA has such an attractive feature that all source signals are separated simultaneously from their mixtures, while the other methods using deflation process extract signals one by one. If the deflation process fails, all the signals cannot be separated. However, the EVA with reference signals enables us to extract all the sources without any deflation methods.

Through computer simulations and real environment experiments, we show the effectiveness of the proposed methods.

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2 Problem Formulation

Throughout this paper, let us consider the following MIMO static system with n inputs and m outputs, a convolutive mixture model with additive noise (See figure 1.);

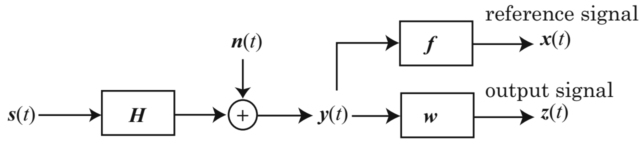


Fig. 1. The composite system of an unknown system and a filter, and reference system

$$\boldsymbol{y}(t) = \sum_k \boldsymbol{H}(k)\boldsymbol{s}(t-k) + \boldsymbol{n}(t), \tag{1}$$

where $\boldsymbol{y}(t)$ represents an m-column output vector called the *observed signal*, $\boldsymbol{s}(t)$ represents an n-column input vector called the *source signal*, $\boldsymbol{n}(t)$ represents an m-column noise vector and $\boldsymbol{H}(t)$ is an $m \times n(m \geq n)$ mixing matrix.

To achieve the blind source separation for the system (1), a convolutive mixture in the time domain is converted into instantaneous mixtures in the frequency domain with the short-time Fourier transform (STFT),

$$\mathbf{Y}(f,t) = \mathbf{H}(f)\mathbf{S}(f,t) + \mathbf{N}(f,t). \tag{2}$$

The following n filters, which are m-input single-output (MISO) static systems driven by the observed signals, are used for each frequency bin:

$$\mathrm{Z}_l(f,t) = \mathbf{w}_l^H(f)\mathbf{Y}(f,t), \quad l = 1,2,\ldots,n, \tag{3}$$

where superscript ^{H} denotes the conjugate transpose (Hermitian) of a matrix or a vector and $\mathrm{Z}_l(f,t)$ is the lth output of the filter, $\mathbf{w}_l(f) = [\mathrm{w}_{l1}(f), \mathrm{w}_{l2}(f), \ldots, \mathrm{w}_{lm}]^H$ is an m-column vector representing the m coefficients of the filter in frequency bin f. Substituting (2) into (3), we obtain

$$\begin{aligned}\mathrm{Z}_l(f,t) &= \mathbf{w}_l^H(f)\mathbf{H}(f)\mathbf{S}(f,t) + \mathbf{w}_l^H(f)\mathbf{N}(f,t),\\ &= \mathbf{g}_l^H(f)\mathbf{S}(f,t) + \mathbf{w}_l^H(f)\mathbf{N}(f,t), \quad l = 1,2,\ldots,n,\end{aligned} \tag{4}$$

where $\mathbf{g}_l(f) = [\mathrm{g}_{l1}(f), \mathrm{g}_{l2}(f), \ldots, \mathrm{g}_{ln}(f)]^H = \mathbf{H}^H(f)\mathbf{w}_l(f)$ is an n-column vector. The BSS problem considered in this paper can be formulated as follows: Find n filters $\mathbf{w}_l(f)$'s denoted by $\tilde{\mathbf{w}}_l(f)$'s satisfying the following condition, without the knowledge of $\mathbf{H}(f)$, even if the Gaussian noise $\mathbf{N}(f,t)$ is added to the observed signal $\mathbf{Y}(f,t)$,

$$\tilde{\mathbf{g}}_l(f) = \mathbf{H}^H(f)\tilde{\mathbf{w}}_l(f) = \tilde{\boldsymbol{\delta}}_l(f), \quad l = 1,2,\ldots,n, \tag{5}$$

where $\tilde{\boldsymbol{\delta}}_l(f)$ is an n-column vector whose elements $\tilde{\delta}_{lr}(f)(r = 1,2,\ldots,n)$ are equal to zero except for $\rho_l(f)$th element.

To solve the blind separation problem, we put the following assumptions on the system and the source signals.

A1) The matrix $\mathbf{H}(f)$ in (2) has full column rank.
A2) The input sequence $\{\mathbf{S}(f,t)\}$ is a zero-mean, non-Gaussian vector whose element processes $\{\mathrm{S}_i(f,t)\}, i=1,2,\ldots,n$, are mutually statistically independent and have nonzero variance, $\sigma^2_{s_i}(f)$ and nonzero fourth-order cumulants, $\gamma_i(f)$, $i=1,2,\ldots,n$.
A3) The noise sequence $\{\mathbf{N}(f,t)\}$ is stationary process vector, whose elements, $\{N_i(f,t)\}, i=1,2,\ldots,m$ are Gaussian processes with zero mean.
A4) The two vector sequences $\{\mathbf{N}(f,t)\}$ and $\{\mathbf{S}(f,t)\}$ are mutually independent.

3 Eigenvector Algorithms (EVAs)

3.1 Analysis of EVAs with the Reference Signal for MIMO Static Systems

In this subsection we assume that there is no noise $\boldsymbol{n}(t)$ in the output $\boldsymbol{y}(t)$. Next we propose the eigenvector algorithm with the reference signal. To solve the BSS problem, the following cross-cumulant between $\mathrm{Z}_l(f,t)$ and the reference signal $\mathrm{X}(f,t)$ is defined:

$$\mathrm{C}_{\mathrm{ZX}}(f) = \mathrm{cum}\{\mathrm{Z}_l(f,t), \mathrm{Z}_l^*(f,t), \mathrm{X}(f,t), \mathrm{X}^*(f,t)\}, \tag{6}$$

where * denotes the complex conjugate and the reference signal $\mathrm{X}(f,t)$ is given by $\mathbf{f}^H(f)\mathbf{Y}(f,t) = \mathbf{f}^H(f)\mathbf{H}(f)\mathbf{S}(f,t) = \mathbf{a}^H(f)\mathbf{S}(f,t)$ ($\mathbf{a}^H(f) = \mathbf{f}^H(f)\mathbf{H}(f)$ is a vector whose elements are $\mathrm{a}_1(f), \mathrm{a}_2(f), \ldots, \mathrm{a}_n(f)$), using an appropriate filter $\mathbf{f}(f)$. The filter $\mathbf{f}(f)$ is called a *reference system*. Moreover we define the constrain $\sigma^2_{\mathrm{Z}_l}(f) = \sigma^2_{S_{\rho_l}}(f)$, where $\sigma^2_{\mathrm{Z}_l}(f)$ and $\sigma^2_{S_{\rho_l}}(f)$ denote the variance of the output $\mathrm{Z}_l(f,t)$ and a source signal $S_{\rho_l}(f,t)$, respectively. In the case of SISO systems, Jelonnek et al. [1,2] have shown that the maximization of $|\mathrm{C}_{\mathrm{ZX}}(f)|$ under $\sigma^2_{\mathrm{Z}_l}(f) = \sigma^2_{S_{\rho_l}}(f)$ leads to a closed-form expression as the following generalized eigenvector problem:

$$\mathbf{C}_{\mathrm{YX}}(f)\mathbf{w}_l(f) = \lambda \mathbf{R}(f)\mathbf{w}_l(f). \tag{7}$$

Then they utilize the facts that $\mathrm{C}_{\mathrm{ZX}}(f)$ and $\sigma^2_{\mathrm{Z}_l}(f)$ can be expressed in terms of the vector $\mathbf{w}_l(f)$ as, respectively,

$$\mathrm{C}_{\mathrm{ZX}}(f) = \mathbf{w}_l^H(f)\mathbf{C}_{\mathrm{YX}}(f)\mathbf{w}_l(f), \tag{8}$$

$$\sigma^2_{\mathrm{Z}_l}(f) = \mathbf{w}_l^H(f)\mathbf{R}(f)\mathbf{w}_l(f), \tag{9}$$

where $\mathbf{C}_{\mathrm{YX}}(f)$ is a matrix whose (i,j)th element is calculated by $\mathrm{cum}\{\mathrm{Y}_i(f,t), \mathrm{Y}_j^*(f,t), \mathrm{X}(f,t), \mathrm{X}^*(f,t)\}$, $\mathbf{R}(f) = E[\mathbf{Y}(f,t)\mathbf{Y}^H(f,t)]$ is the covariance matrix of m-column vector $\mathbf{Y}(f,t)$ and λ is an eigenvalue of $\mathbf{R}^\dagger(f)\mathbf{C}_{\mathrm{YX}}(f)$, where $\dagger$ denotes the pseudo-inverse operation of a matrix. Moreover they have shown that the eigenvector corresponding to the maximum eigenvalue of $\mathbf{R}^\dagger(f)\mathbf{C}_{\mathrm{YX}}(f)$ becomes the solution of the blind equalization problem in

[1,2], which is referred to as an *eigenvector algorithm* (EVA). However, the algorithm proposed by Jelonnek et al. is for SISO or SIMO infinite impulse response channel. Therefore, we want to show how the eigenvector algorithm (7) works for the BSS in the case of the MIMO static system in the frequency domain. To this end, we use following equalities:

$$\mathbf{R}(f) = \mathbf{H}(f)\mathbf{\Sigma}(f)\mathbf{H}^H(f), \tag{10}$$

$$\mathbf{C}_{\mathrm{YX}}(f) = \mathbf{H}(f)\mathbf{\Lambda}(f)\mathbf{H}^H(f), \tag{11}$$

where $\mathbf{\Sigma}(f)$ is a diagonal matrix whose elements are $\sigma_{s_i}^2(f), i = 1, 2, \ldots, n$ and $\mathbf{\Lambda}(f)$ is a diagonal matrix whose elements are $|\mathrm{a}_i(f)|^2\gamma_i(f), i = 1, 2, \ldots, n$. Then we obtain the following theorem.

Theorem 1. *Suppose the values* $|\mathrm{a}_i(f)|^2\gamma_i(f)/\sigma_{s_i}^2(f), i = 1, 2, \ldots, n$ *are all nonzero and distinct. If the noise* $\mathbf{N}(f,t)$ *is absent in (2), the* n *eigenvectors corresponding to* n *nonzero eigenvalues of* $\mathbf{R}^\dagger(f)\mathbf{C}_{\mathrm{YX}}(f)$ *become the the vectors* $\tilde{\mathbf{w}}_l(f)$*'s satisfying (5).*

Proof. Based on (7), we consider the following eigenvector problem:

$$\mathbf{R}^\dagger(f)\mathbf{C}_{\mathrm{YX}}(f)\mathbf{w}_l(f) = \lambda\mathbf{w}_l(f). \tag{12}$$

Then substituting (10) and (11) into (12), we obtain

$$\mathbf{H}^{H\dagger}(f)\mathbf{\Sigma}^{-1}(f)\mathbf{H}^\dagger(f)\mathbf{H}(f)\mathbf{\Lambda}(f)\mathbf{H}^H(f)\mathbf{w}_l(f) = \lambda\mathbf{w}_l(f). \tag{13}$$

Since $\mathbf{H}(f)$ has full column rank, using a property of the pseudo-inverse operation([3], p.433),

$$\mathbf{H}^{H\dagger}(f)\mathbf{\Sigma}^{-1}(f)\mathbf{\Lambda}(f)\mathbf{H}^H(f)\mathbf{w}_l(f) = \lambda\mathbf{w}_l(f). \tag{14}$$

Multiplying (14) by $\mathbf{H}^H(f)$ from left side and using a property of the pseudo-inverse operation again, (14) becomes

$$\mathbf{\Sigma}^{-1}(f)\mathbf{\Lambda}(f)\mathbf{H}^H(f)\mathbf{w}_l(f) = \lambda\mathbf{H}^H(f)\mathbf{w}_l(f). \tag{15}$$

By noting that $\mathbf{\Sigma}^{-1}(f)\mathbf{\Lambda}(f)$ is a diagonal matrix whose elements, $|\mathrm{a}_i(f)|^2\gamma_i(f)/\sigma_{s_i}^2(f), i = 1, 2, \ldots, n$ are all nonzero and distinct, if $\mathbf{g}_l(f) = \mathbf{H}^H(f)\mathbf{w}_l(f) \neq \mathbf{0}$, then the eigenvector $\mathbf{g}_l(f)$ obtained from (15) becomes the vector $\tilde{\mathbf{g}}_l(f)$ satisfying (5). Namely, the n eigenvectors $\mathbf{w}_l(f)$ corresponding to n nonzero eigenvalues of $\mathbf{R}^\dagger(f)\mathbf{C}_{\mathrm{YX}}(f)$ obtained from (12) become the vectors $\tilde{\mathbf{w}}_l(f)$ satisfying (5). □

3.2 Robust Eigenvector Algorithm (REVA)

In the previous subsection, we assume that there are no noises in the output signals. In this subsection, we shall show such an eigenvector algorithm that the solutions (5) can be obtained, even if the noise $\boldsymbol{n}(t)$ is present in the output

$\boldsymbol{y}(t)$. To this end, we introduce fourth-order cumulants matrices of m-column vector process $\{\mathbf{Y}(f,t)\}$, which constitute a set of $m \times m$ matrices $\mathbf{C}_{\mathbf{Y},i}(f), i = 1,2,\ldots,m$. The matrix $\mathbf{C}_{\mathbf{Y},i}(f)$ is defined by

$$[\mathbf{C}_{\mathbf{Y},i}(f)]_{q,r} = \mathrm{cum}\left\{\mathrm{Y}_q(f,t), \mathrm{Y}_r^*(f,t), \mathrm{Y}_i(f,t), \mathrm{Y}_i^*(f,t)\right\}, \tag{16}$$

where $[\cdot]_{q,r}$ denotes the (q,r)th element of the matrix $\mathbf{C}_{\mathbf{Y},i}(f)$. Then we consider an $m \times m$ matrix $\mathbf{Q}(f)$ expressed by

$$\mathbf{Q}(f) = \sum_{i=1}^{m} \mathbf{C}_{\mathbf{Y},i}(f). \tag{17}$$

It is shown by a simple calculation (see [4]) that (17) becomes

$$\mathbf{Q}(f) = \mathbf{H}(f)\tilde{\mathbf{\Lambda}}(f)\mathbf{H}^H(f), \tag{18}$$

where $\tilde{\mathbf{\Lambda}}(f)$ is a diagonal matrix defined by

$$\tilde{\mathbf{\Lambda}}(f) = \mathrm{diag}\{\gamma_1(f)\tilde{\mathrm{a}}_1(f), \gamma_2(f)\tilde{\mathrm{a}}_2(f), \ldots, \gamma_n(f)\tilde{\mathrm{a}}_n(f)\}, \tag{19}$$

$$\tilde{\mathrm{a}}_r(f) = \sum_{i=1}^{m} \mathrm{h}_{ir}(f)\mathrm{h}_{ir}^*(f), \quad r = 1,2,\ldots,n, \tag{20}$$

and $\mathrm{diag}\{\cdots\}$ denotes a diagonal matrix with the diagonal elements built from its arguments, $\mathrm{h}_{ir}(f)$ is the (i,r)th element of $\mathbf{H}(f)$.

Here, as a constraint, we take the following value:

$$\begin{aligned} |\mathrm{C}_{\mathrm{ZY}}(f)| &= \left|\sum_{i=1}^{m} \mathrm{cum}\{\mathrm{Z}_l(f,t), \mathrm{Z}_l^*(f,t), \mathrm{Y}_i(f,t), \mathrm{Y}_i^*(f,t)\}\right| = \left|\mathbf{w}_l^H(f)\mathbf{Q}(f)\mathbf{w}_l(f)\right| \\ &= \left|\sum_{i=1}^{m} \tilde{\mathrm{a}}_i(f)\gamma_i(f)\mathrm{g}_{li}(f)\mathrm{g}_{li}^*(f)\right|. \end{aligned} \tag{21}$$

Then, we consider solving the problem that the fourth-order cumulants $|\mathrm{C}_{\mathrm{ZX}}(f)|$ is maximized under the condition that $|\mathrm{C}_{\mathrm{ZY}}(f)| = |\tilde{\mathrm{a}}_{\rho_l}(f)\gamma_{\rho_l}(f)|$. Then by the Lagrangian method, the following generalized eigenvector problem is derived from the problem:

$$\mathbf{C}_{\mathrm{YX}}(f)\mathbf{w}_l(f) = \tilde{\lambda}\mathbf{Q}(f)\mathbf{w}_l. \tag{22}$$

From the following theorem, by solving the eigenvector problem of the matrix $\mathbf{Q}^\dagger(f)\mathbf{C}_{\mathrm{YX}}(f)$, the n eigenvectors $\mathbf{w}_l(f) (l = 1,2,\ldots,n)$ correspond to the vectors $\tilde{\mathbf{w}}_l(f) (l = 1,2,\ldots,n)$ in (5).

Theorem 2. *Suppose the values* $|\mathrm{a}_i(f)|^2/\tilde{\mathrm{a}}_i(f), i = 1,2,\ldots,n$ *are all nonzero and distinct. The* n *eigenvectors corresponding to* n *nonzero eigenvalues of* $\mathbf{Q}^\dagger(f)\mathbf{C}_{\mathrm{YX}}(f)$ *become the the vectors* $\tilde{\mathbf{w}}_l(f)$*'s satisfying (5).*

Proof. We omit the proof because it is easily proved as well as Theorem 1.

Remark 1. Since the matrix $\mathbf{Q}^{\dagger}(f)\mathbf{C}_{\mathrm{YX}}(f)$ consists of only the fourth-order cumulants, the eigenvector derived from the matrix can be obtained with as little influence of Gaussian noises as possible, which is referred as a *robust eigenvector algorithm* (REVA).

4 Adaptive Version of REVA

REVA can be implemented adaptively. To this end we must specify the dependency of each time t and omit frequency bin f for simplicity. We show the update procedure in the case of 2-input 2-output static system.

$\tilde{\mathbf{Q}}(t)$, which is the estimator of $\mathbf{Q}$ at time t is calculated by

$$\tilde{\mathbf{Q}}(t) = \alpha\tilde{\mathbf{Q}}(t-1) \\ +(1-\alpha)\left\{\left(\mathbf{C}_1(t) - \tilde{\mathbf{C}}_1(t) - \mathrm{tr}\{\tilde{\mathbf{C}}_1(t)\}\right)\mathbf{C}_1(t) - \tilde{\mathbf{C}}_2(t)\mathbf{C}_2^*(t)\right\}, \quad (23)$$

where α is a forgetting factor close to, but less than 1 and $\mathrm{tr}\{X\}$ denotes the trace of matrix X.

Here $\mathbf{C}_1(t)$ and $\mathbf{C}_2(t)$ in (23) are defined by $\mathbf{C}_1(t) = \mathbf{Y}(t)\mathbf{Y}^H(t)$ and $\mathbf{C}_2(t) = \mathbf{Y}^*(t)\mathbf{Y}^H(t)$, respectively. $\tilde{\mathbf{C}}_1(t)$ and $\tilde{\mathbf{C}}_2(t)$ are the moving averages of $\mathbf{C}_1(t)$ and $\mathbf{C}_2(t)$, respectively, which are calculated by

$$\tilde{\mathbf{C}}_1(t) = \beta\tilde{\mathbf{C}}_1(t-1) + (1-\beta)\mathbf{C}_1(t), \quad (24)$$

$$\tilde{\mathbf{C}}_2(t) = \beta\tilde{\mathbf{C}}_2(t-1) + (1-\beta)\mathbf{C}_2(t), \quad (25)$$

where β is also a forgetting factor close to, but less than 1 and $\alpha > \beta$.

$\tilde{\mathbf{C}}_{\mathrm{YX}}(t)$, which is the estimator of $\mathbf{C}_{\mathrm{YX}}$ at time t is calculated by

$$\tilde{\mathbf{C}}_{\mathrm{YX}}(t) = \alpha\tilde{\mathbf{C}}_{\mathrm{YX}}(t-1) + (1-\alpha)\{\mathbf{Y}(t)\mathbf{Y}^H(t)\mathrm{X}(t)\mathrm{X}^*(t) - \mathbf{Y}(t)\mathbf{Y}^H(t)\tilde{\mathrm{V}}_{\mathrm{X}}(t) \\ -\mathbf{Y}(t)\mathrm{X}(t)\tilde{\mathbf{V}}_{\mathrm{Y}_1}(t) - \mathbf{Y}(t)\mathrm{X}^*(t)\tilde{\mathbf{V}}_{\mathrm{Y}_2}(t)\}, \quad (26)$$

where $\tilde{\mathrm{V}}_{\mathrm{X}}(t)$ and $\tilde{\mathbf{V}}_{\mathrm{Y}_i}(t), i = 1, 2$ are the moving averages of $\mathrm{V}_{\mathrm{X}}(t)$ and $\mathbf{V}_{\mathrm{Y}_i}(t)$ defined by

$$\tilde{\mathrm{V}}_{\mathrm{X}}(t) = \beta\tilde{\mathrm{V}}_{\mathrm{X}}(t-1) + (1-\beta)\mathrm{V}_{\mathrm{X}}(t), \quad (27)$$

$$\tilde{\mathbf{V}}_{\mathrm{Y}_i}(t) = \beta\tilde{\mathbf{V}}_{\mathrm{Y}_i}(t-1) + (1-\beta)\mathbf{V}_{\mathrm{Y}_i}(t), \quad i = 1, 2, \quad (28)$$

where $\mathrm{V}_{\mathrm{X}}(t) = \mathrm{X}(t)\mathrm{X}^*(t)$, $\mathbf{V}_{\mathrm{Y}_1}(t) = \mathrm{Y}^H(t)\mathrm{X}^*(t)$ and $\mathbf{V}_{\mathrm{Y}_2}(t) = \mathrm{Y}^H(t)\mathrm{X}(t)$.

Then the separator $\mathbf{w}_l(t)$ is calculated by solving eigenvector problem (7).

5 Experiments

5.1 Simulation

We conducted a simulation experiment. $\mathbf{H}(z)$, which is z-transform of the mixing matrix $\boldsymbol{H}(t)$, is defined as:

$$\mathbf{H}(z) = \begin{pmatrix} 1 - 0.4z^{-1} & 0.5z^{-1} - 0.2z^{-2} \\ 0.5z^{-1} - 0.2z^{-2} & 1 - 0.4z^{-1} \end{pmatrix}. \quad (29)$$

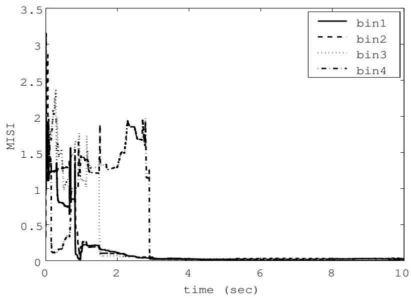


Fig. 2. MISIs of EVA

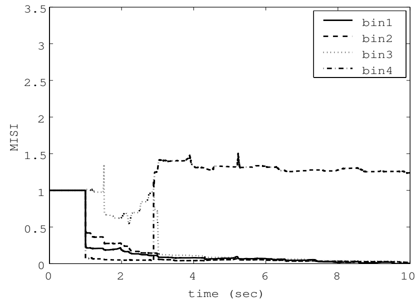
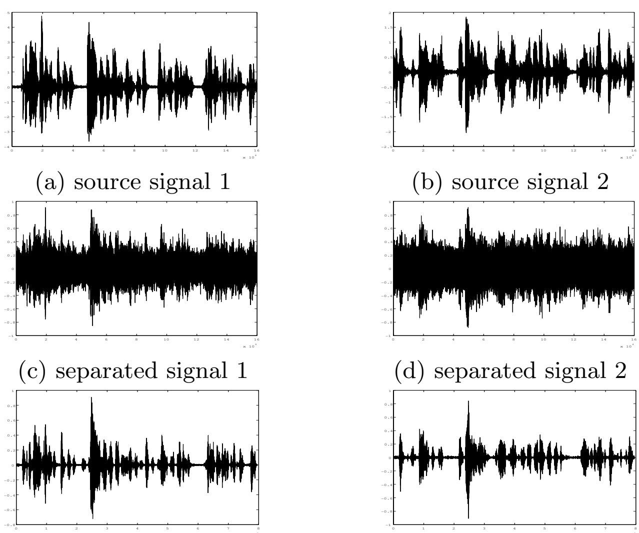


Fig. 3. MISIs of SEM

The BSS problem is solved by adaptive REVA. To measure the separation performance, multichannel intersymbol-interference (MISI) was used, which is defined as

$$\mathrm{MISI} = \sum_{i=1}^{2} \left(\frac{\sum_{j=1}^{2} |\mathrm{g}_{ij}|^2}{\max_j |\mathrm{g}_{ij}|^2} - 1 \right) + \sum_{j=1}^{2} \left(\frac{\sum_{i=1}^{2} |\mathrm{g}_{ij}|^2}{\max_i |\mathrm{g}_{ij}|^2} - 1 \right). \qquad (30)$$

The MISI becomes zero if $\tilde{\mathbf{g}}_l$'s satisfying (5) are obtained. The smaller the MISI value is, the closer the obtained solution is to the desired one. Figure 2 shows the MISIs of some frequency bins using EVA with the reference signal and Figure 3 shows those of SEM [5], which uses the deflation process. Obviously



(a) source signal 1 (b) source signal 2

(c) separated signal 1 (d) separated signal 2

(e) enhanced signal 1 (f) enhanced signal 2

Fig. 4. Waveforms of source, separated and enhanced signals

using SEM the deflation process failed in a frequency bin, while EVA with the reference signal could converge to the desired solution in all frequency bins.

Remark 2. REVA utilizes the fourth-order cumulants. To estimate the fourth-order cumulants accurately a large number of samples are generally needed. Therefore it takes a rather long time to converge using REVA.

5.2 Real Environment

In an office room, we conducted separation experiments using REVA. Because the reference signal is needed, the number of microphones is three, while the number of source is two, one of the observed signals is used as a reference signal. Manually 5dB Gaussian noises are added to the observed signals to show that the proposed REVA works in a noisy environment. Figure 4 shows a set of waveforms of the source signals, the separated signals and the enhanced signals which were given by the ES 202 050 software [6]. In the enhanced signals additive Gaussian noises were reduced. We can see that REVA can extract independent but distorted source signals.

6 Conclusion

We described the BSS problem in the frequency domain. We proposed the eigenvector algorithm (EVA) with reference signals. The proposed method has such an attractive property that all source signal are extracted simultaneously without the deflation process. EVA can be robust to Gaussian noises using only the higher-order cumulants (REVA). We have also shown the adaptive version of REVA.

The computer simulations and real environment experiments have clarified the validity of the proposed methods.

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