Convolutional independent component analysis by leave-one-out optimal kernel approximation

Jiann-Ming Wu†, Shih-Hua Lee

Abstract—This work addresses on blind separation of convolutive mixtures of independent sources. The temporally convolutive structure is assumed to be composed of multiple mixing matrices, each corresponding to a time delay, collectively transforming a segment of consecutive source signals to form multichannel observations. As $\tau = 1$, this problem reduces to linear independent component analysis. For arbitrary $\tau$, we propose a new algorithm to estimate the unknown convolutive structure as well as independent sources. The proposed convolutive ICA algorithm is based on optimal kernel estimation and leave-one-out approximation operated under the mean-field-annealing process. We test the new algorithm with artificially created data and two-microphone recordings of speech and music. It is shown that the error between the estimated and given convolutive structures is significantly reduced for artificially created data and the human speech is well separated from the background music for the two-microphone recordings. The proposed new algorithm is empirically shown effective for blind separation of convolutive mixtures of independent sources.

Keywords—Convolutie mixture, independent component analysis, blind separation, optimal kernel estimation, leave-one-out approximation, K-state transfer function, mean field annealing.

I. INTRODUCTION

In this work, we will discuss blind separation [1][2][3][10][16] of convolutive mixtures of independent sources. The temporally convolutive structure is assumed to consist of multiple mixing matrices, each corresponding to a time delay, collectively transforming a segment of consecutive source signals to form multichannel observations,

$$\mathbf{x}[t] = \sum_{i=0}^{\tau-1} \mathbf{B}_i \mathbf{s}[t-i], t \geq \tau$$

(1)

where $\mathbf{B}_i$ is an invertible mixing matrix and all $\mathbf{s}[t]$ denote a sample from $d$ independent sources. The mixing model in equation (1) consists of multiple square matrices, each transforming $\mathbf{s}[t-i]$ to $\mathbf{x}[t]$ with $i$ running from 0 to $\tau-1$.

A. Independent component analysis

As $\tau = 1$, equation (1) reduces to the following linear mixture structure

$$\mathbf{x}[t] = \mathbf{B} \mathbf{s}[t],$$

(2)

and contains no temporal convolution. The relevant blind separation task translates to typical independent component analysis (ICA) [4][7][13][14], which is aimed to retrieve original source signals by a de-mixing process,

$$\mathbf{y}[t] = \mathbf{W} \mathbf{x}[t],$$

(3)

where $\mathbf{W}$ denotes a de-mixing matrix. If $\mathbf{W}$ is identical to the inverse of $\mathbf{B}$ or WB is a permutation of an identity matrix, $\mathbf{y}[t]$ would essentially represent the original source. That is

$$\mathbf{y}[t] = \text{WB}s[t] = (\mathbf{B}^{-1}) \mathbf{B}[t] = \mathbf{s}[t]$$

(4)

where $\mathbf{P}$ is a permutation of an identity matrix.

Blind separation insists on recovering source signals from given observations. The "blind" means that nothing is known about the source signals or mixing structure. The only hypothesis is source signals are independent. Let observation be $\mathbf{X} = \{\mathbf{x}[t] \in \mathbb{R}^m\}_{t=1}^T$, independent source $\mathbf{S} = \{\mathbf{s}[t] \in \mathbb{R}^n\}_{t=1}^T$, and mixing matrix $\mathbf{A} \in \mathbb{R}^{m \times n}$. Equation (2) represents the simplest noiseless model of blind separation, which is equivalent to independent component analysis and aimed to retrieve the original source signals by equation (3-5). But as instantaneous linear mixtures, the observation oriented from above model is formed without temporal convolution. The linear mixture model is actually far from real formation of interesting signals, such as sound recordings. The model in equation (1) is stated to produce linear convolutive mixtures of independent sources. Its inverse problem is termed as convolutive independent component analysis, whose goal is to retrieve independent sources from given observations without informations about the linear convolutive mixing structure.

B. Convolutional independent component analysis

For arbitrary $\tau > 1$, the blind separation task is termed as convolutive independent component analysis, and is here resolved by the proposed recurrent optimal kernel method which iteratively estimates convolutive filters and independent sources following leave-one-out approximation along a mean-field-annealing process [9][12]. The mixing model in equation (1) can be rewritten as follows,

$$x_n[t] = \sum_{m=1}^d A_{nm} \tilde{s}_m[t],$$

(6)

where $x_n[t]$ denotes an instance from the $n$th channel of observations, $A_{nm}$ is a column vector of $\tau$ elements, representing a convolutive filter kernel and

$$\tilde{s}_m[t] = (s_m[t-\tau+1], s_m[t-\tau+2], \ldots, s_m[t])^T.$$

We show the proposed recurrent optimal kernel method able to recover the unknown convolutive mixing structure as well as independent sources. For blind separation of convolutive mixtures of independent sources, proposed method executes leave-one-out approximation under the mean-field-annealing process, and uses $K$-state transfer functions [15] to compensate for uncertainty of unknown source signals determined intermediately. There are some discussions about 2-state [11] and $K$-state transfer function in the later section.

By numerical simulations, we test the proposed method with artificially created data and real world observations, such as recordings of speech and music signals. The result shows significant improvement by the proposed method for convolutive ICA against existing ICA algorithms [4][7][13][14].
II. Leave-one-out optimal kernel approximation

Since the convolutive structure has a great influence on formation of observations, its estimation is very crucial for retrieving independent sources. The convolutive structure that emulates transmission of an independent source to a channel of observations is associated with a linear kernel. The optimal kernel based method that operates following the strategy of leave-one-out approximation is shown feasible for blind separation of convolutive mixtures of independent sources.

A. Optimal kernel estimation

Assume

\[ x[t] = \sum_{i=0}^{\tau-1} A_i s[t-i] + n[t] \]  

(7)

where all \( n[t] \) denote Gaussian noises with zero mean and a small common variance, and \( \{A_i \in \mathbb{R}\}_{i=0}^{\tau-1} \) denotes a linear kernel. Given one observation \( \{x[t] \in \mathbb{R}\}_{t=1}^{T} \), and one source \( \{s[t] \in \mathbb{R}\}_{t=1}^{T} \), optimal estimation aims to find a linear kernel which minimizes the following mean square error

\[ E(A_i) = \frac{1}{T} \sum_{t=1}^{T} [x[t] - \sum_{i=0}^{\tau-1} A_i s[t-i]]^2, \]

where the noise \( n[t] \) is approximated by

\[ \hat{n}[t] = x[t] - \sum_{i=0}^{\tau-1} A_i s[t-i]. \]  

(8)

To minimize \( E \), we set

\[ \frac{\partial E}{\partial A_j} = 0, j = 0, \ldots, \tau - 1 \]

Calculating the partial derivative of \( E \) with respect to each \( A_i \),

\[ \frac{\partial}{\partial A_j} \frac{1}{T} \sum_{t=1}^{T} [x[t] - \sum_{i=0}^{\tau-1} A_i s[t-i]]^2 = 0, j = 0, \ldots, \tau - 1, \]

we have the following linear equation,

\[ \sum_{t=1}^{T} x[t] s[t-j] = \sum_{i=0}^{\tau-1} A_i \sum_{t=1}^{T} s[t-i] s[t-j], j = 0, \ldots, \tau - 1 \]

(9)

Let \( \mathbf{b} \) be a column vector with elements denoted by

\[ b_j = \sum_{t=j+1}^{T} x[t] s[t-j]. \]

\( \mathbf{Q} \) be a matrix with rows denoted by

\[ \mathbf{Q}_{j+1} = \left( \sum_{t=j+1}^{T} s[t] s[t-j] \quad \cdots \quad \sum_{t=j}^{T} s[t - \tau + 1] s[t-j] \right), \]

where \( j \) runs from 0 to \( \tau - 1 \), \( \mathbf{A} \) be a matrix with rows denoted by \( A_j \). We reform the linear equation (9) as follows

\[ \mathbf{b} = \mathbf{Q} \mathbf{A}. \]  

(10)

If \( \mathbf{Q} \) is non-singular, we get

\[ \mathbf{A} = \mathbf{Q}^{-1} \mathbf{b}. \]  

(11)

Otherwise the optimal kernel could be approximated by

\[ \mathbf{A} = \mathbf{Q} \left( \mathbf{Q}^T \mathbf{Q} \right)^{-1} \mathbf{Q} \mathbf{b}. \]  

(12)

For multi-channel sources, we rewrite equation (7) as

\[ x[t] = \sum_{i=0}^{\tau-1} (A_{i1} s_1[t - i] + \cdots + A_{id} s_d[t - i]) + n[t] \]

\[ = \sum_{i=0}^{\tau-1} A_i s_i[t - i] + n[t] \]  

(13)

where

\[ \{s_i [t] \in \mathbb{R}\}_{t=1}^{T}, l = 1, \ldots, d \]

denotes \( d \) independent sources and

\[ \{A_i \in \mathbb{R}\}_{i=0}^{\tau-1}, l = 1, \ldots, d \]

denotes a linear kernel through which \( d \) sources are transmitted to form the observation. The optimal kernel estimation is applicable for the case with multiple sources. In this occasion, the correspondent matrices \( \mathbf{Q} \) and \( \mathbf{b} \) in the right hand side of equation (11-12) can be further expressed.

B. Leave-one-out approximation

The source signals and mixing structure are unknown for blind separation [16]. Following the mixing model in equation (6), multi-channel observations are convolutive mixtures of independent sources. For real situation, each of them may be assumed to have its own dominant source. Following the assumption, subtracting from a single channel observation approximation of non-dominant sources through an optimal kernel estimation could achieve a dominant source. The recurrent optimal kernel method is proposed for blind separation of convolutive mixtures of independent sources. The proposed method operates as an iterative process, by which all of currently-estimated independent sources are separately updated in a random sequence at each iteration. For each observation, the correspondent dominant source is set to compensate for the approximating error of the other intermediate non-dominant sources. The proposed method is summarized by the following stepwise procedure and shown in figure 2.

1. Given observations \( \{\mathbf{X}_l\}_{l=1}^{4} \), where \( \mathbf{X}_l \) denotes the \( l \)th channel observation with length \( T \),

\[ \mathbf{X}_l = \{X_l[t], \ldots, X_l[T]\}. \]

2. Set \( \mathbf{S}_i(\theta) = \mathbf{X}_l \) for \( i = 1, \ldots, d \), and \( l = 1 \), where \( \mathbf{S}_i(l) \) denotes the \( d \)th independent source estimated at \( l \)th iteration,

\[ \mathbf{S}_i(l) = \{S_{i,j}[t], \ldots, S_{i,j}[T]\}. \]

3. For \( i = 1 \) to \( d \),

(a) Approximate \( X_i[t] \) by \( \sum_{j<i} A_{i,j} \tilde{S}_j(l,t) + \sum_{j>i} A_{i,j} \tilde{S}_j(l-1,t) \) and use the equations (10-12) to determine all \( A_{i,j} \) with \( j \neq i \), where \( \tilde{A}_{i,j} \) is a column vector of \( \tau \) elements and

\[ \tilde{S}_j(l,t) = (S_{j,i}[t - \tau + 1], S_{j,i}[t - \tau + 2], \ldots, S_{j,i}[T]), \]

where \( t = 1, \ldots, T \).

(b) Set \( S_{i,j}[t] = X_i[t] - \sum_{j<i} \tilde{A}_{i,j} \tilde{S}_j(l,t) - \sum_{j>i} \tilde{A}_{i,j} \tilde{S}_j(l-1,t) \).

4. \( l = l + 1 \). If a halting condition holds, i.e.

\[ \frac{1}{L} \sum_{l=1}^{L} \left| \mathbf{S}_i(l) - \mathbf{S}_i(l-1) \right| < 10^{-6}, \]

terminate, otherwise goto step 3..
C. Mean field annealing

Mean field annealing is employed to improve performance of the proposed recurrent optimal kernel method. This section introduces two transfer functions to compensate for uncertainty of independent sources estimated by leave-one-out approximation and shows effectiveness of the annealed version for blind separation of convolutive mixtures of independent sources by numerical simulations.

C.1 Two-state transfer function

Since both the convolutive mixing structure and independent sources are unknown in advance for blind separation, uncertainty of estimated sources is modeled by the following Boltzmann assumption

\[
\Pr \{ \tilde{s}[t] = \pm 1 \} \propto \exp(\pm \beta s[t]),
\]

where \( \{s[t]\} \) denotes instances derived at step 3. of the procedure presented in the previous subsection, and \( \{\tilde{s}[t]\} \) denotes collection of instances with compensation for uncertainty of source estimation. In the annealed version, the uncertainty of source estimation is inversely modulated by the parameter \( \beta \), which is scaled gradually from sufficiently low to high values. Since the outcome of \( \tilde{s}[t] \) has been restricted within \( \{\pm 1\} \) according to the assumption (14), we have the following equation,

\[
\Pr (\tilde{s}[t] | s[t]) = \frac{\exp(\beta s[t] \tilde{s}[t])}{\exp(\beta s[t]) + \exp(-\beta s[t])}
\]

The conditional expectation of \( \tilde{s}[t] \) is expressed as follows,

\[
g(s[t]) \equiv \langle \tilde{s}[t] | s[t] \rangle = \Pr (\tilde{s}[t] = I | s[t]) - \Pr (\tilde{s}[t] = -I | s[t]) = \exp(\beta s[t]) - \exp(-\beta s[t]) = \tanh(\beta s[t])
\]

When \( \beta = 1 \), the conditional expectation is identical to the output of the hyperbolic tangent function in responding to \( s[t] \).

The mean-field-annealing process increases \( \beta \) from sufficiently low to high values. When \( \beta \) is set sufficiently high, \( g(s[t]) = I \) or \( -I \) for \( s[t] \in \mathbb{R} \). The mean-field-annealing process tends to cause binary independent components.

C.2 K-state transfer function

As shown in Figure 1, the K-state transfer function (15) consists of \( K \) distinct knots, collectively denoted by \( c = \{c_1, c_2, \ldots, c_K\} \), which are employed to partition the range of external fields, \( (c_{\min}, c_{\max}) \), into \( K \) non-overlapping intervals, each being represented by

\[
i_k = \left( \frac{c_k + c_{k-1}}{2}, \frac{c_k + c_{k+1}}{2} \right), \quad \text{for } k = 1, \ldots, K,
\]

where \( c_0 = c_{\min} \) and \( c_{K+1} = c_{\max} \) denote two auxiliary knots for boundary conditions, and \( c_k < c_{k+1} \) is assumed for non-decreasing ordering. It follows that

\[
\bigcup_{k=1}^{K} i_k = (c_{\min}, c_{\max}),
\]

and \( i_i \cap i_j = \emptyset \) for all \( i \neq j \). The K-state transfer function (15) is defined by

\[
\theta_K(h[t]; c) = e_k^h \text{ if } h[t] \in i_k
\]

in response to an external field \( h[t] \), where \( e_k^h \) is a standard unitary vector. \( E_K = \{ e_k^h \}_{k=1}^{K} \) represents a standard basis for \( \mathbb{R}^K \).

A stochastic \( K \)-state transfer function is stated to have a stochastic output in response to an external field. Let \( \delta \) be a unitary random vector with outcomes belonging the set \( E_K \). Assume

\[
\Pr (\delta = e_k^h | h) \propto \exp(-\beta \|h - c_k\|^2),
\]

which implies

\[
\Pr (\delta = e_k^h | h) = \frac{\exp(-\beta \|h - c_k\|^2)}{\sum_{l} \exp(-\beta \|h - c_l\|^2)}
\]

The expectation of \( \delta \) conditional to \( h = h[t] \) can be derived as follows,

\[
g_k(h[t]; c) \equiv \langle \delta | h = h[t] \rangle = \sum_{k=1}^{K} e_k^h \Pr (\delta = e_k^h | h = h[t]) = \frac{\exp(-\beta \|h - c_k\|^2)}{\sum_{l} \exp(-\beta \|h - c_l\|^2)}
\]

The product of a \( K \)-state transfer function and its knot vector expressed by

\[
g(h[t]) = c' g_K(h[t]; c)
\]

is employed to compensate for uncertainty of estimated independent sources. The change of the \( g \) function along an annealing process is shown in Figure 1.

III. CONVOLUTIVE INDEPENDENT COMPONENT ANALYSIS

The model of linear convolutive mixtures discussed in this section is expressed by equation (6) with \( \tau > 1 \). For convolutive independent component analysis, multi-channel observations, \( \{X_i(t)\}_{i=1}^{d} \), are assumed to be linear mixtures of a segment of consecutive source signals with temporal convolution. Let \( X_i \) denote the \( i \)th channel observation. \( S_i(t) \) denote the \( i \)th independent source recovered at \( t \)th iteration, where \( i = 1, \ldots, d \). Given observations \( \{X_i(t)\}_{i=1}^{d} \), convolutive independent component analysis is aimed to retrieve \( S_1, \ldots, S_d \). The recurrent optimal kernel method is improved by the mean-field-annealing process for blind separation. The details of the annealed convolutive ICA algorithm are summarized as follows.

1. Given observations \( \{X_i(t)\}_{i=1}^{d} \), where \( X_i \) denotes the \( i \)th channel observation with length \( t \),

\[
X_i = \{X_i[1], \ldots, X_i[T]\}.
\]

2. Set \( S_i(\theta) = X_i \) for \( i = 1, \ldots, d \), and \( l = 1 \), where \( S_i(l) \) denotes the \( i \)th independent source estimated at \( t \)th iteration,

\[
S_i(l) = \{S_i[1], \ldots, S_i(l)[T]\}.
\]

3. For \( i = 1 \) to \( d \),

(a) Approximate \( X_i(t) \) by \( \sum_{j<i} A_{ij} S_j(t, l) + \sum_{j>i} A_{ij} S_j(t - l, t) \) and use the equations (10-12) to determine all \( A_{ij} \) with \( j \neq i \), where \( A_{ij} \) is a column vector of \( \tau \) elements and

\[
\bar{S}_j(l, t) = \{S_{j,i}[t - \tau + 1], S_{j,i}[t - \tau + 2], \ldots, S_{j,i}[t]\}.
\]
where $t = 1, \ldots, T$.

(b) Set $S_i(t) = X_i(t) - \sum_{j \neq i} A_{ij} S_j(t)$.

(c) Set $h = S_i(l)$ and update $S_i(l+1) = g(h)$ by equation (18).

Increasing $\beta$ by an annealing schedule and go to step 3, until a terminating condition is satisfied, i.e.

$$\frac{j}{T} \sum_{t} g_k(h[t]; c)^T g_k(h[t]; c) > 0.7$$

by equation (17).

IV. NUMERICAL SIMULATIONS

We first test the optimal kernel estimation for signal approximation, and then show effectiveness of the proposed convolutive ICA algorithm for blind separation of convolutive mixtures of independent sources. Artificial source data, $s[t] = (s_1[t], s_2[t], s_3[t], s_4[t])^T$

$$= \begin{pmatrix}
\text{sign}(\cos(2\pi t/155)) \\
\sin(2\pi t/800) \\
\sin(2\pi t/300 + 6 \cos(2\pi t/60)) \\
\sin(2\pi t/90)
\end{pmatrix},$$

for $t = 1, \ldots, 2000$,

which have been used by Amari et al. in [1] serve as independent signals. We use matlab programs to simulate the proposed convolutive ICA algorithm and test its effectiveness for blind separation of artificially created observations and real world sound recordings.

A. Signal approximation

If a single channel observation is known to be linear mixtures of a set of independent sources, given both the observation and sources, the optimal kernel estimation characterized by equation (10-12) for signal approximation is aimed to estimate the unknown mixing structure. The artificial source data $s[t]$ used in this subsection are shown in Figure 3. All $A_k$ in equation (13) are generated randomly and uniformly with $n[t] = 0$ for all distinct $\tau$. Through the randomly created mixing structure, independent sources form one channel observation $x[t]$. Then by equation (10-12) we can estimate all $A_k$ for signal approximation. For different $\tau$ and source signals, numerical simulations of the optimal kernel estimation for signal approximation are described as follows.

1. $\tau = 10$: If four channel source signals are employed

$$s[t] = \begin{pmatrix}
\text{sign}(\cos(2\pi t/155)) \\
\sin(2\pi t/800) \\
\sin(2\pi t/300 + 6 \cos(2\pi t/60)) \\
\sin(2\pi t/90)
\end{pmatrix}$$

to generate one channel observation. The mean square error between the given observation and approximating signal is listed at the first row of Table I.

2. $\tau = 20$: The same experiment is repeated for $\tau = 20$. The mean square error between the given observation and the approximating signal are given in the second row of Table I.

3. $\tau = 50$: The same experiment is repeated for $\tau = 50$, and the mean square errors between the given observation and the obtained approximation are listed in Table I.

### Table I

<table>
<thead>
<tr>
<th>Artificial source data</th>
<th>Mean square error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Four channel source signals $\tau = 10$</td>
<td>5.372647e-009</td>
</tr>
<tr>
<td>Four channel source signals $\tau = 20$</td>
<td>2.507220e-008</td>
</tr>
<tr>
<td>Four channel source signals $\tau = 50$</td>
<td>5.692306e-008</td>
</tr>
</tbody>
</table>

B. Convolutive independent component analysis

In this subsection, we test the proposed convolutive ICA algorithm with both artificial data and recordings of music and speech. In the artificial data, all observations are convolutive mixtures of independent sources $s[t]$ through the mixing model of equation (6) with $d = 4$ and $\tau = 1, \ldots, 6$. The recordings of music and speech were downloaded from the homepage provided by the author of the work [3]. The two sources are respectively oriented from the speech of a man from one to ten in English and rock musics. There are two microphones for recording these signals simultaneously. The recordings are modeled as convolutive mixtures of independent source signals with $d = 2$ and $\tau = 61$ through the structure described in equation (6).

#### B.1 Artificial data

All of the randomly generated $A_{nm}$ in equation (6) are restricted to be diagonally dominated and non-negative. To reduce influence in amplification of observations, we normalize all $A_{nm}$ such that $||A_{nm}|| = 1$. Each channel of observations is dominated by a distinct channel of source. By the proposed convolutive ICA algorithm, blind separation of convolutive mixtures of independent sources with variant $\tau$ are described as follows, where the parameters in equation (17-18) used in numerical simulations are listed in Table II. With $\tau = 6$ the linear convolutive mixtures of artificial source data are shown in Figure 4, and the recovered sources are shown in Figure 5.

#### Table II

| Parameters used in the convolutive ICA algorithm for variant $\tau$. |
|------------------------|------------------|
| $\tau = 1$ | 41 [-1, 1] | 995 | 81.1256 |
| $\tau = 2$ | 41 [-1.25, 1.25] | 931 | 80.5000 |
| $\tau = 3$ | 41 [-1.5, 1.5] | 894 | 81.5313 |
| $\tau = 4$ | 41 [-1.75, 1.75] | 851 | 82.1094 |
| $\tau = 5$ | 41 [-2] | 834 | 82.5156 |
| $\tau = 6$ | 41 [-2.25, 2.25] | 828 | 83.2031 |

B.2 Blind separation of real world signals

The proposed convolutive ICA algorithm is shown effective for blind separation of real world signals shown in Figure 7. We will use the proposed convolutive ICA algorithm to separate background musics from speeches of a man, trying to erase specific signals for noise cancellation. We use matlab programs to read recording signals, and the amplification of output signals is between $-1$ and $1$. Figure 6 shows the recording of two microphones. The peak in the figure is the speech of a man and the background music appears not oscillating strongly. The result of separation is shown in Figure 7, where we can clearly identify speech of a man and background music. In this case, we set $K = 2l$ and $c \in [-1, 1]$ for numerical simulations.
V. Conclusions

Traditional linear independent component analysis algorithms [4]-[7],[13],[14] are known ineffective for blind separation of convolutive mixtures of independent sources. This work approaches convolutive independent component analysis by an annealed recurrent optimal kernel method. In the proposed method, leave-one-out approximation is operated to leave one source out of the mixing structure. Such way is apparently different from the approach in the previous work. Although preliminary results of numerical simulations for artificial data analysis are not as well as our expectation, we amend the algorithm with the $K$-state transfer function and mean field annealing to get better results. In numerical simulations for artificial data analysis, we have shown effectiveness of the proposed algorithm for the case with the time delay $\tau$ from $1$ to $6$. When $\tau$ increases over $5$, the recovered source that corresponds to the $3$th channel signal $\sin(2\pi t/300 + 6 \cos(2\pi t/60))$ still has little distortion.

In blind separation of recordings of music and speech, we have successfully resolved the two-source and two-observation real world problem.

To achieve better results, we have applied mean filed annealing and $K$-state transfer function to improve the proposed recurrent optimal kernel method for convolutive independent component analysis. But it still costs a lot of time when the dimension of observations is large. Except for adjusting parameters in the proposed method to speed up the process, we could make a balance between time and quality. There would be more issues of two-state transfer function and $K$-state transfer function for trade-off of time and quality.

Signals in real world are not always measured without temporal convolution. When measuring signals, equipments can not receive each signal simultaneously. Certainly there exists a temporally convolutive structure in transmitting source signals to observations. That is why we focus on convolutive independent component analysis whose mixing structure has a great potential for modeling formation of real world signals.

References


Fig. 1. $K$-state transfer function in an annealing schedule

Optimal kernel updating

Fig. 2. Leave-one-out approximation with recurrent optimal kernel method
Fig. 3. Artificial independent source data. (A) $\text{sign} \left( \cos \left( \frac{2\pi t}{155} \right) \right)$. (B) $\sin \left( \frac{2\pi t}{800} \right)$. (C) $\sin \left( \frac{2\pi t}{300} + 6 \cos \left( \frac{2\pi t}{60} \right) \right)$. (D) $\sin \left( \frac{2\pi t}{90} \right)$. $t = 1, \ldots, 2000$.

Fig. 4. Linear convolutive mixtures of 4 independent sources with $\tau = 6$.

Fig. 5. Recovering sources by convolutive ICA with $\tau = 6$.

Fig. 6. The recordings of music and speech were downloaded from the homepage provided by the author of the work [3].

Fig. 7. Separated music and speech by convolutive ICA with $\tau = 61$. 