A COMPARISON OF INDEPENDENT COMPONENT AND INDEPENDENT SUBSPACE ANALYSIS ALGORITHMS

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ABSTRACT

Recent advances in separation of convolutive mixtures of audio signals have shown that the problem can be successfully solved in time-domain in a multistep procedure including an application of some method of instantaneous independent component analysis (ICA) or independent subspace analysis (ISA), as one of the steps. In this paper we propose a test that allows a comparison of different ICA and ISA algorithms from this perspective. The test consists in evaluating separation of a pseudo-convolutive mixture of given independent signals. The mixture has features of real-world convolutive mixtures and of instantaneous mixtures simultaneously. We apply the proposed test to compare performance of several ICA and ISA algorithms in four different scenarios, taking in mind that suitability of the algorithms depends on properties of the separated signals.

1. INTRODUCTION

In this paper, we aim at comparing different ICA/ISA methods when applied to blind audio source separation (BASS), which is a popular discipline in recent decade due to emerging applications in multi-microphone systems. The goal of BASS is to separate simultaneously sounding audio sources that are mixed in a natural acoustical environment through the convolutive model

$$x_i(n) = \sum_{j=1}^{d} \sum_{\tau=0}^{M_{ij}-1} h_{ij}(\tau) s_j(n-\tau), \quad i = 1, \ldots, m, \tag{1}$$

where $x_1(n), \ldots, x_m(n)$ are the observed signals on microphones, $s_1(n), \ldots, s_d(n)$ are the unknown original sources, and h_{ij}'s are source-microphone impulse responses each of length M_{ij}. The original sources can be estimated by passing the mixture through a separating (de-mixing) filter

$$\widehat{s}_i(n) = \sum_{j=1}^{m} \sum_{\tau=0}^{L-1} w_{ij}(\tau) x_j(n-\tau), \quad i = 1, \ldots, d. \tag{2}$$

of a finite length L.

A popular way is to ground the separation on the assumption that the original sources are statistically independent. The solution of the problem is then based on methods related to the ICA [1]. However, original ICA methods assume instantaneous mixture, i.e., when $M_{ij} = 1$ for all i, j. The problem given by (1), therefore, needs to be transformed. This is usually done either in the frequency-domain [2] or in the time-domain [3]. In general, performance of the BASS algorithms can be evaluated e.g. by aid of the BSS_eval toolbox [4]. In this paper, we propose a special method of comparison of different ICA and ISA algorithms, with respect to their performance *inside* a *time-domain* BSS method.

In the time-domain methods, the convolution operation is written in terms of a vector/matrix product. In particular, the output of the separating filter in (2) corresponds to a direction in the subspace spanned by rows of an $mL \times (N_2 - N_1 + 1)$ matrix

$$\mathbf{X} = \begin{bmatrix} x_1(N_1) & \ldots & \ldots & x_1(N_2) \\ x_1(N_1-1) & \ldots & \ldots & x_1(N_2-1) \\ \vdots & \vdots & \vdots & \vdots \\ x_1(N_1-L+1) & \ldots & \ldots & x_1(N_2-L+1) \\ x_2(N_1) & \ldots & \ldots & x_2(N_2) \\ x_2(N_1-1) & \ldots & \ldots & x_2(N_2-1) \\ \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ x_m(N_1-L+1) & \ldots & \ldots & x_m(N_2-L+1) \end{bmatrix}, \tag{3}$$

where N_1 and $N_2, N_2 > N_1$, determine part of recorded signals used to define $\mathbf{X}$.

Time-domain BASS methods seek for such a linear transform that splits the row-space of $\mathbf{X}$ to independent subspaces so that each of them corresponds to a separated audio signal. To separate the subspaces, it is possible to use some algorithm for Independent Subspace Analysis (ISA) [5, 6, 7]. Another way is to apply one of large number of known ICA algorithms to estimate several one-dimensional components of each original source [8, 3, 9], and the subspaces are obtained by a suitable grouping (clustering) of the components [6, 9]. It was shown in [9] that under some condition, even quite short filters ($L = 10\ldots40$) can produce effective separation results.

Since the applied ICA/ISA algorithm is the hearth of the time-domain separation, a natural question is which one is suited best for that purpose. The objective evaluation of the decomposition of $\mathbf{X}$ is however an intricate problem due to

1. unpredictable performance limitations caused by the finite length of separating filters (the finite number of rows of $\mathbf{X}$), and

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2. an ambiguity of optimal solution, because the original signals can be retrieved up to unknown filterings [10].

Note that both the features affect the achieved signal-to-interference ratio [4].

In the following section, we propose a test that is designed so that the above problems are avoided, and the evaluation is done through a criterion tailored to the test. In Section 3, we discuss usefulness of several ICA models and select representative methods for experimental comparison by the proposed test that is described in Section 4. Sections 5-6 provide ranking of the methods and suggest conclusions.

2. TEST PROPOSAL

The main idea of the test is to define a source matrix of the original sources $s_1(n),\ldots,s_d(n)$ as

$$\mathbf{S} = \begin{bmatrix} s_1(N_1) & \ldots & \ldots & s_1(N_2) \\ s_1(N_1-1) & \ldots & \ldots & s_1(N_2-1) \\ \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ s_d(N_1-L+1) & \ldots & \ldots & s_d(N_2-L+1) \end{bmatrix}. \quad (4)$$

The mixture is then simply given by

$$\mathbf{X} = \mathbf{AS}, \quad (5)$$

where $\mathbf{A}$ is a regular $dL \times dL$ matrix. The matrix can have the block Sylvester structure as it exists in the true convolutive mixtures [8, 3].

Unlike the true convolutive mixture in (3), the mixture in (5) can, in theory, be separated perfectly by $\mathbf{W} = \mathbf{A}^{-1}$. By contrast, the common feature is that ICA or ISA methods applied to (5) tend to produce arbitrarily filtered counterparts of $s_1(n),\ldots,s_d(n)$, because rows of $\mathbf{S}$ corresponding to delayed versions of the same source are *not* independent due to temporal structures of original (audio) sources.

2.1 Choice of the mixing matrix A

Most of ICA and ISA algorithms (all that were included in our comparative study) are equivariant. This means that outcome of the separation is essentially the same (up to the order of components or subspaces) if the input data are mixed by an arbitrary regular mixing matrix. It follows that it makes no difference if the mixing matrix in simulations has a certain structure or not. However, if someone wants to study a separation algorithm that relies on the special structure of the mixing matrix, a fair comparison would be obtained only if the mixing matrix has the same structure.

2.2 Grouping of components

Let ISA/ICA algorithms under the test be applied to the mixture $\mathbf{X}$. ISA algorithms produce d independent L-dimensional subspaces, which only have to be properly reordered to fit the original signal order. ICA algorithms yield one-dimensional components that have yet to be grouped. In our test, we do not want to let the choice of the grouping procedure interfere with the estimated quality of the separation. Therefore we resort to the optimum grouping of the components subject to the signal-to-interference ratio (SIR) both for ICA and ISA algorithms.

Consider the SIR of the jth separated component, denoted by $c_j(n)$, with respect to the ith source. Since $c_j(n)$ was obtained as the jth row of

$$\mathbf{C} = \widehat{\mathbf{W}}\mathbf{X} = \widehat{\mathbf{W}}\mathbf{AS} \stackrel{\text{def.}}{=} \mathbf{GS}, \quad (6)$$

it can be written as a linear combination of $s_i(n)$ and its time delays plus the remainder, which represents the interference. Thus, the SIR can be defined as

$$\mathrm{SIR}_j^i = \frac{\hat{\mathrm{E}}[\sum_{\ell=1}^{L} \mathbf{G}_{j,(i-1)L+\ell}\, s_i(n-\ell+1)]^2}{\hat{\mathrm{E}}[c_j(n) - \sum_{\ell=1}^{L} \mathbf{G}_{j,(i-1)L+\ell}\, s_i(n-\ell+1)]^2}, \quad (7)$$

where $\hat{\mathrm{E}}$ stands for the sample mean operator, and $\mathbf{G}_{j,k}$ are elements of the so-called gain matrix $\mathbf{G}$.

Now, for each source s_i we assign those L separated components c_j that have the largest SIR_j^i.

2.3 Criteria

Once we have the components assigned to the sources, we can judge quality of the separation. We propose two ways. First, we measure the distance of the true and estimated subspaces in terms of the angle of these subspaces in the vector space spanned by all rows of the matrix $\mathbf{S}$ in (5). In Matlab it is realized by the command `subspace`.

Second, we propose an alternative way which goes one step further towards the estimation of the source signals, using the time-shift structure of the matrix $\mathbf{S}$.

Let J_i denote a set of the indices of components that were assigned to the ith source. Then, an estimate of the ith source delayed by ℓ samples, i.e. of $s_i(n-\ell)$, can be obtained, avoiding unknown permutations in $\mathbf{G}$, through the *inverse* of $\mathbf{G}$ as

$$\widehat{s}_i^{\ell}(n) = \sum_{j\in J_i} (\mathbf{G}^{-1})_{(i-1)L+\ell,j}\, c_j(n), \quad (8)$$

for $\ell = 0,\ldots,L-1$, and these estimates of $s_i(n-\ell)$ can be combined together by simple time-shifting and averaging,

$$\widehat{s}_i(n) = \frac{1}{L}\sum_{\ell=1}^{L} \widehat{s}_i^{\ell}(n+\ell)\ . \quad (9)$$

The resultant reconstructed signal $\widehat{s}_i(n)$ is then written in the form signal-plus-interference, and the corresponding SIR yields the final criterion for the overall estimation of the ith source. Note that $\widehat{s}_i(n) = s_i(n)$ if and only if $\mathbf{G}$ is exactly block-diagonal (up to the order of its rows). Therefore, the SIR of $\widehat{s}_i(n)$ reflects the error of the block blind separation in a comprehensive way!

Another important point to note here is that the values SIR_j^i, $j \in J_i$, in (7) do *not* provide objective measures for evaluating the overall separation of $s_i(n)$ because of an unknown filtering of the respective components.

A third alternative of computing the SIR of the subspaces was advocated in [8]. It consists in applying a SIMO blind identification method to each subspace. This approach has the disadvantage that it introduces another source of error in the SIR computation.

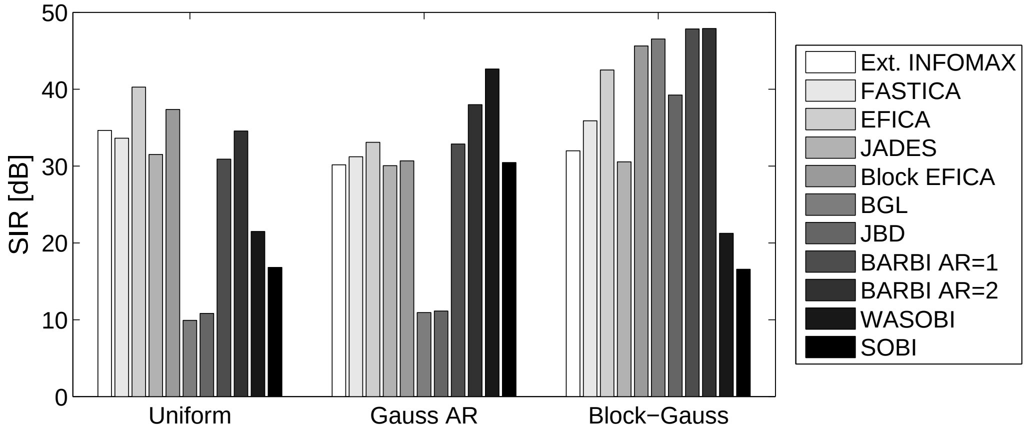

Figure 1: SIR of three separated artificial signals mixed via (4-5) with $L = 3$ averaged over 100 independent trials. Note that both settings of BARBI (first and second-order block-AR model) yield good results in this example.

3. REPRESENTATIVE METHODS

The main ICA algorithms for separation of instantaneous mixtures are based either on non-Gaussianity, distinct coloration (spectral diversity), or non-stationarity. While the first class uses higher-order statistics (nonlinear transforms) of the data, the other two classes are based on second-order statistics. Recently, combinations of the models have been considered, also [3, 13, 14, 21].

We note that the non-Gaussianity based methods tend to produce temporally whitened versions of $s_1(n),\ldots,s_d(n)$. The whitened signals are sometimes called the partial innovations. The reason is that the innovations of each sources and their mutual time-shifted copies are usually the most non-Gaussian signals that can be obtained by linear transformations of the data.

In our experiments, we consider Extended Infomax [11], FastICA [1] (the symmetric approach with "tanh" nonlinearity), EFICA [15], and SJADE [20] as the representatives for this class. Unlike the other methods, SJADE is an ISA algorithm.

Methods relying on nonstationarity divide mixed signals in non-overlapping segments of a given length, compute signal covariance matrices on each segment, and do an approximate joint diagonalization (AJD) of these matrices. These methods cannot separate sources having the same variance profiles. Hence, they cannot distinguish delayed copies of the same source as the delays are negligible compared to the length of segments. Separated components of (5) thus form clusters of arbitrarily filtered original sources, which is required for the separation. The class is represented by BGL [12] and JBD [7] algorithms. While BGL searches one-dimensional components, JBD is an ISA algorithm.

Methods relying on spectral diversity of the signals are based on (block-)AJD of cross-covariance matrices of mixed signals. In simulations, we shall consider the earlier and popular SOBI algorithm [16] and its weight-adjusted version WASOBI [17].

We will also consider methods that combine the basic ICA models, namely, Block EFICA [18] combining the non-Gaussianity with the nonstationarity, and the recently proposed BARBI algorithm [19, 21] combining the nonstationarity and the spectral diversity principles via block AR modeling of signals.

4. EXPERIMENTS

First, we present a simple example with three artificial signals obeying the basic ICA models: a non-Gaussian i.i.d. signal that is uniformly distributed, a stationary Gaussian process with AR coefficients $(1, 0.7)$, and a nonstationary block-Gaussian white signal whose each of four blocks has, respectively, the variance 1, 0.09, 0.01, and 1.21. These signals were used to form (4) with $L = 3$, which was mixed by a randomly generated mixing matrix via (5). Then, ICA methods were applied to separate the mixture and the resulting signals were evaluated by the proposed SIR.

Results of this example shown in Fig. 1 confirm characteristic features of the selected methods. Extended INFOMAX, FastICA, SJADE, EFICA, and Block EFICA succeeded to roughly separate all signals, because the 1^{st} signal is non-Gaussian, the 3^{rd} nonstationary signal behaves like being non-Gaussian, and one signal is allowed to be Gaussian, which is the 2^{nd} one. BGL and JBD failed to separate the 1^{st} and 2^{nd} signals since they have the same dynamic profiles. SOBI and WASOBI separated the 1^{st} and 3^{rd} signals poorly due to their similar spectra. Finally, BARBI succeeded to separate all signals since the 1^{st} and 2^{nd} signals have different spectra and different dynamics from that of the 3^{rd} signal.

In our main experiment, we did extensive testing of algorithms by separating the convolutive-like mixtures of two audio sources. Four different combinations of acoustical signals each of length 6.5s (10^5 samples) sampled at 16kHz were considered. In two scenarios, we mixed a male and a female speech and two speeches of the same male speaker, respectively, which stands for the situation where speakers' voices have different and similar spectra. In the fourth and third scenario, the male speech was mixed with a musical signal: First, with a long synthesizer tone having almost static variance, and, second, with a piece of a rhythmic music.

To simulate Monte-Carlo trials, we used the method of sliding time-window gradually shifted throughout the whole recordings. In each trial, the time-window of length 8000

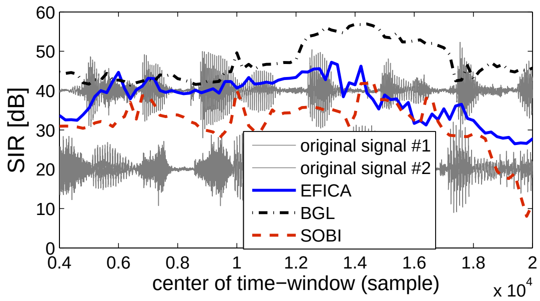

Figure 2: Example of course of the SIR averaged over two separated signals.

samples (0.5s) was shifted by 200 samples (12.5ms, i.e., there are 461 trials in each scenario), and the matrix (4) was constructed from the corresponding segment of signals with $L = 10$ and multiplied by a random mixing matrix. Then, the mixture was separated by the ICA and ISA methods mentioned in the previous section, with the following parameters: Block EFICA, BGL, JBD and BARBI had the number of blocks set to 40 (so that each block had the length 200). The methods based on spectral diversity, computed the separation by AJD of 11 covariance matrices with time lags $0, 1, \ldots, 10$.

Due to lack of space we present results in terms of the SIR only; results obtained by angles between subspaces were similar. An example of the resulting course of SIR is shown in Fig. 2.

The evolutions of resulting SIRs are indicative of the behavior of respective algorithms when signals are changing in time. Therefore, we use the three following characteristics of the SIR for evaluation: (A) the mean value, (B) the standard deviation, and (C) the mean of absolute value of variation, which is the difference between SIRs achieved in two successive time-windows. These characteristics of SIR are shown in Table 1 in the form $A \pm B(C)$.

Note that "good" performance must be characterized by continuous behavior of the resulting SIR in time. The range of SIR corresponds with the standard deviation B, and the speed of changes is reflected by the mean variation C. Higher value of the latter criterion signifies unstable performance. Conversely, small C and B means stable performance that is less dependent on signal characteristics.

5. DISCUSSION

5.1 Methods based on non-Gaussianity

Performances of algorithms using non-Gaussianity (INFOMAX, FastICA, EFICA, SJADE) appear to be not the best of all algorithms, but are quite good in all scenarios. EFICA slightly outperforms the other algorithms (INFOMAX, FastICA, and SJADE) thanks to being more advanced. All these four algorithms were outperformed by Block EFICA, which, in addition to the non-Gaussianity, utilizes non-stationarity of the signals as well.

5.2 Methods based on non-stationarity

These methods gave the best separation results in our study. Among them, BGL and JBD are based on non-stationarity only, BARBI combines it with the spectral diversity. Here, BGL and BARBI with AR order 1 appear to be the most successful algorithms. It is interesting to compare the results in Table 1 with results in [19] that deals with a separation of an *instantaneous* mixture of speech signals. In the latter study, BARBI was a clear winner, outperforming the other algorithms (including the BGL) by several dB. In this comparative study, both methods give similar results. Hence we can see that there is a qualitative difference between the instantaneous mixtures and the pseudo-convolutive mixtures. BARBI with AR order 2 was less successful both in our study and in separating the instantaneous mixtures of speech signals [19].

5.3 Methods based on spectral diversity

We observe that WASOBI fails in many trials in all scenarios, the results of SOBI are stable, moreover, SOBI yields surprisingly good results in the third scenario. This is another example showing the difference between instantaneous and pseudo-convolutive mixtures, because WASOBI is normally known to outperform SOBI in separating instantaneous mixtures [17]. In order to explain the failure of WASOBI, we note that blocks of cross-covariance matrices of (4) are *not* diagonally dominant except for the zero-lag cross-covariance. Therefore the AJD procedure in WASOBI might terminate at transformed matrices that are "more diagonal" in a sense but "less block-diagonal" than they should be.

5.4 Comparison of ICA and ISA algorithms

Our comparative study does not show any clear advantage of subspace (ISA) algorithms (JBD, SJADE) over the ICA algorithms. In order to make sure that the difference between the algorithms is not only in the separation criteria, we also compared performance of the ISA algorithms with their ICA versions. The ICA versions were obtained by setting the subspace dimensions equal to one. The separation results of the ISA algorithms and their ICA variants were approximately the same; the truly subspace algorithms were only faster.

6. CONCLUSION

We have proposed a method of comparing performance of different ICA and ISA methods in time-domain separation of convolutive mixtures of audio sources. In our test, the best separation results were obtained by the BGL and BARBI algorithms. Note, however, that the results depend, in general, on properties of the to-be separated signals.

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METHOD	**SIR** [dB] female speech male speech #1	 male speech #2 male speech #1	 music #1 male speech #1	 music #2 male speech #1	average comp. time per trial (secs)
Ext. INFOMAX	29.6±7.8(1.9) 30.4±7.8(1.8)	31.3±6.0(1.8) 30.3±6.1(1.5)	30.1±7.6(2.4) 28.2±6.3(1.5)	31.5±8.1(1.7) 31.4±8.1(1.8)	13.5
FastICA	30.4±6.6(1.3) 31.8±6.4(1.5)	31.8±5.8(1.5) 30.6±5.5(1.4)	29.4±10.6(*6.5*) 31.4±5.0(1.7)	33.6±6.5(1.7) 33.9±4.7(1.4)	0.65
EFICA	32.7±7.0(1.8) 36.9±6.5(2.2)	34.1±6.3(1.9) 34.4±6.1(2.0)	35.9±6.2(2.8) 33.4±6.1(1.5)	34.6±5.5(1.8) 36.7±6.1(1.7)	1.06
SJADE	25.3±6.3(1.5) 26.4±6.5(1.7)	27.9±6.2(1.7) 26.4±7.0(1.7)	33.4±6.1(2.2) 26.8±4.5(1.1)	28.4±5.0(1.3) 28.3±4.6(1.3)	6.0
Block EFICA	35.0±8.4(2.2) 36.2±6.8(2.2)	36.4±7.9(2.0) 33.8±7.1(1.8)	34.2±6.9(3.1) **35.1**±8.2(2.1)	35.2±6.1(1.8) 39.0±8.3(1.8)	2.98
BGL	**41.2**±7.6(1.2) **43.8**±5.2(1.1)	**41.8**±8.5(1.3) **40.1**±6.3(1.1)	36.8±7.3(2.2) **37.1**±10.0(1.2)	**40.8**±5.8(1.1) **42.5**±8.1(1.1)	0.046
JBD	27.8±8.0(1.1) 30.7±6.6(1.4)	30.6±7.6(1.4) 29.1±7.4(1.2)	**38.5**±7.0(2.0) 29.4±7.9(1.1)	33.8±8.0(1.1) 31.5±7.1(1.3)	10.68
BARBI AR=1	**42.3**±8.2(1.4) **42.5**±7.1(1.6)	**42.4** ±7.3(2.2) **41.4**±7.5(2.2)	34.9±7.6(4.8) 16.8±13.8(*6.9*)	**38.7**±6.5(2.1) **43.9**±9.6(1.8)	0.059
BARBI AR=2	15.0±15.8(*15.0*) 12.8±14.7(*14.4*)	17.4±14.6(*15.0*) 13.1±13.4(*14.8*)	7.8±10.8(*11.4*) 3.6±10.1(*10.7*)	20.6±16.0(*15.1*) 20.1±13.3(*12.5*)	0.092
WASOBI	29.2±10.2(*9.3*) 27.0±11.7(*11.0*)	25.1±9.4(*9.5*) 23.3±10.8(*10.1*)	28.4±14.9(*16.5*) 9.4±12.0(*13.3*)	33.2±11.8(*10.1*) 32.0±10.2(*7.6*)	0.17
SOBI	25.9±7.3(2.0) 25.2±7.1(2.1)	21.9±8.0(2.3) 20.7±7.6(2.2)	**46.0**±5.9(2.1) 32.4±4.0(1.0)	37.5±6.0(1.6) 33.1±4.7(1.3)	3.24

Table 1: Separation SIR obtained by the ICA and ISA algorithms in four pseudoconvolutive mixtures. The best two mean values are written in bold, and the mean variations above 5dB are written in italic. The test was running in Matlab^{TM} v7.2 on a PC with i7-920 processor, 2.66GHz, 3GB RAM.

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