Adaptive Blind Separation of Instantaneous Linear Mixtures of Independent Sources

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Abstract. In many applications, there is a need to blindly separate independent sources from their linear instantaneous mixtures while the mixing matrix or source properties are slowly or abruptly changing in time. The easiest way to separate the data is to consider off-line estimation of the model parameters repeatedly in time shifting window. Another popular method is the stochastic natural gradient algorithm, which relies on non-Gaussianity of the separated signals and is adaptive by its nature. In this paper, we propose an adaptive version of two blind source separation algorithms which exploit non-stationarity of the original signals. The results indicate that the proposed algorithms slightly outperform the natural gradient in the trade-off between the algorithm's ability to quickly adapt to changes in the mixing matrix and the variance of the estimate when the mixing is stationary.

1 Introduction

Blind separation of instantaneous mixtures of independent signals or independent component analysis (ICA) usually assumes that a mixing matrix and source signals are stationary. In practice, however, the mixing matrix may vary in time - for example in audio signal separation, the audio scene may change in time, speakers may move, or there are some other changes in the environment.

Traditional methods of the blind source separation (BSS) can be adapted to such cases by applying them to time-shifting windows. There is always a trade-off between adaptability of the algorithms to changes of the mixing systems and accuracy (stability) of the estimation when the mixing matrix is constant. Such trade-off can be controlled through one or more tuning parameters, often called step size or forgetting factor. Some of the first BSS methods were adaptive [1–3].

In this paper, we design algorithms to blindly and adaptively separate linear instantaneous mixtures of signals that are non-stationary or, more precisely, piecewise stationary with varying variances in different blocks (also called

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epochs) of data. We compare their performance to the widely used stochastic natural gradient algorithm (NG) [4], which is adaptive by its nature and separates the independent signals based on the assumption of their non-Gaussianity. In fact, NG is the most popular method applied in the frequency domain BSS algorithms [5]. The algorithms proposed in this paper are adaptive versions of BGSEP (Block Gaussian SEParation) [6] and of BARBI (Block AutoRegressive Blind Identification) [7]. Both BGSEP and BARBI are based on approximate joint diagonalization of matrices [8]. BARBI is more complex and works with covariance matrices of lag 1, also.

The cause of the gain in performance is that the piecewise stationary modeling of the speech signals is more appropriate for the blind separation than the pure non-Gaussianity. We support the above empirical observation by a theoretical analysis. We compare expressions characterizing the best achievable separation accuracy (Cramer-Rao-induced bounds) obtained trough separation based on non-Gaussianity, and similar expressions for separation based on non-stationarity. However, the performance depends on the degree of non-stationarity of the separated signals.

Next, we compare the performance of a non-Gaussianity based EFICA [9] and non-stationarity-based BGSEP and BARBI when they are applied to mixtures of short speech signals. Then, in Sect. 3, we describe the stochastic natural gradient algorithm and present details of the proposed algorithms, adaptive BGSEP and adaptive BARBI. Section 4 contains simulation results and Sect. 5 concludes the paper.

2 Signal Model and Separation Performance Limits

In this paper, we consider for simplicity squared instantaneous mixtures of independent signals

$$\mathbf{x}_t = \mathbf{A}\mathbf{z}_t, \quad t = 1 \dots T, \tag{1}$$

where $\mathbf{A}$ is an $N \times N$ mixing matrix, which may be constant or slowly varying in time, and $\mathbf{z}_t = [\mathbf{z}_{1t}, \dots, \mathbf{z}_{Nt}]^T$ is the vector of the separated signals.

Below we consider three models of the separated signals:

1. **Non-Gaussianity:** $\mathbf{z}_{nt}$ are i.i.d with zero mean, unit variance. We shall assume that mean square score function of the probability density exists and is finite,
$$\kappa_n = \mathrm{E}\left[\left((\partial \log(p_n(x))/\partial x)^2\right)\right] < \infty, \tag{2}$$
where $p_n(x)$ is the probability density function of the distribution of $\mathbf{z}_{nt}$.
2. **Non-Stationarity:** The observation period $t = [1, \dots, T]$ can be divided into M epochs of equal size, T/M, such that on each epoch m, the $\mathbf{z}_{nt}$ is Gaussian-distributed with zero mean and variance s_{nm}, $m = 1, \dots, M$ for $t = (m-1)T/M + 1, \dots, mT/M$.
3. **Piecewise AR(1) modeling:** The observation period is divided into M epochs, and within each the signal is Gaussian AR(1) process with zero mean, variance s_{nm} and an autoregressive coefficient $\rho_{nm} = \mathrm{E}[z_{nt} z_{n,t+1}]/s_{nm}$ for $n = 1, \dots, N$ and $t = (m-1)T/M + 1, \dots, mT/M$.

There are many methods of the independent component analysis relying on the source non-Gaussianity, see, e.g., [10–13] and references therein. A few BSS methods relying on the source non-stationarity exist, see e.g. [14].

The separation performance can be measured in terms of the estimated interference-to-signal ratio (ISR) matrix, which tells how much energy of the jth original signal is contained in the kth estimated signal.

The ISR matrix can be estimated by examining statistical properties of the separated signals. In particular, for the non-Gaussianity model it was shown in [15] that the ISR matrix elements are lower bounded by the Cramer-Rao-induced bound as

$$\mathrm{ISR}_{jk} \geq \frac{1}{N} \frac{\kappa_k}{\kappa_j \kappa_k - 1}. \tag{3}$$

Note that it was shown that $\kappa_j \geq 1$ for all distribution functions $p_j(x)$, and the equality holds if and only if (iff) $p_j(x)$ is Gaussian. This observation is in accord with the well known fact that the mixture of two random signals is separable (ISR is finite) iff at least one of the probability distributions is non-Gaussian.

For the non-stationarity model it can be shown in a similar way as in [16] that the ISR matrix elements are lower bounded by the Cramer-Rao-induced bound as

$$\mathrm{ISR}_{jk} \geq \frac{1}{N} \frac{\phi_{kj}}{\phi_{jk}\phi_{kj} - 1} \frac{\sum_{m=1}^{M} s_{mj}}{\sum_{m=1}^{M} s_{mk}}, \tag{4}$$

where

$$\phi_{jk} = \frac{1}{M} \sum_{m=1}^{M} \frac{s_{mj}}{s_{mk}}. \tag{5}$$

It can be easily shown that the product $\phi_{jk}\phi_{kj}$ is always greater or equal to one, and it is equal to one if the variances of the separated signals are multiples each of the other, $s_{mj} = \alpha s_{mk}$ for some α and all $m = 1, \ldots, M$. The last fraction in (4) is the ratio of average powers of the jth and kth signal.

Similarly, for the piecewise AR(1) models, the bound on ISR_{jk} has the same form as in (4). The difference resides in the definition of ϕ_{jk}, which is

$$\phi_{jk} = \frac{1}{M} \sum_{m=1}^{M} \frac{s_{mj}}{s_{mk}} \frac{1 + \rho_{km}^2 - 2\rho_{km}\rho_{jm}}{1 - \rho_{jm}^2}. \tag{6}$$

Note that both the models 2 and 3 (non-stationarity and block AR(1) modeling) lead effectively to non-Gaussian signals, so that the principle of non-Gaussianity is a valid approach to decompose the signals. The overall probability distribution function of the data in model 2 and 3 is a mixture of Gaussian, and therefore it is non-Gaussian unless the variances in the blocks are the same. The statistical dependence of the signal in different times is ignored in this model. Parameter κ for the mixture of Gaussians is hard to handle analytically, but we can compute it by numerical integration. Assume that the signal can be divided into 100 epochs and that variances of a signal in the epochs are uniformly distributed in the interval $[1 - \Delta, 1 + \Delta]$, where Δ is a free parameter from the interval $[0, 1]$. We can consider a mixture of two signals of the same type. For Δ close to zero, the signals are nearly stationary and hard to separate for both methods. For Δ close to 1, the separation is more accurate, as we can see in Fig. 1. We can observe the difference in performance about 10 dB.

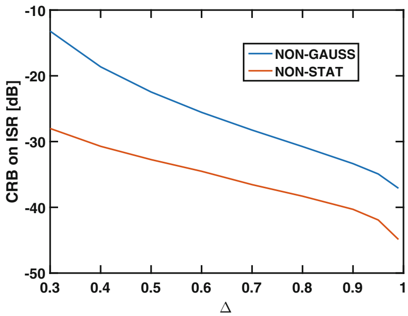

Fig. 1. Cramer-Rao bound on ISR for separation of two piecewise stationary signals with variances uniformly distributed in the interval $[1 - \Delta, 1 + \Delta]$ versus Δ for the signal length $N = 10000$.

Next, we compare performance of one non-Gaussianity-based method and two non-stationarity-based methods in the following experiment. We consider the set of 16 speech signals from [17]. Assuming that the mixing can be considered to be stationary for a second, we take pairs of one second long pieces of different signals, mix them together with a fixed mixing matrix $\mathbf{A} = [1, -0.5; 0.5, 1]$ and demix them blindly with three BSS algorithms: EFICA, as a representative of non-Gaussianity based algorithms, BGSEP and BARBI(1), both with the block length of 200 samples. In total, we did 8 trials (with different beginnings) of all $16.15/2 = 120$ pairs of signals. In Fig. 2(a) we plot the cumulative distribution functions of the achieved ISR for the three methods. We can see that the ISR varies in the range -20 dB to -100 dB, and statistically, there are gaps between the ISR of EFICA, BGSEP and BARBI(1) of 5 dB and another 5 dB, respectively. The BARBI(1) achieves the best separation with BGSEP following and EFICA performing the worst.

Next, we have repeated the same experiment with shorter signals, of the half length, 0.5 s. The difference in performance becomes smaller, as we can see in Fig. 2(b).

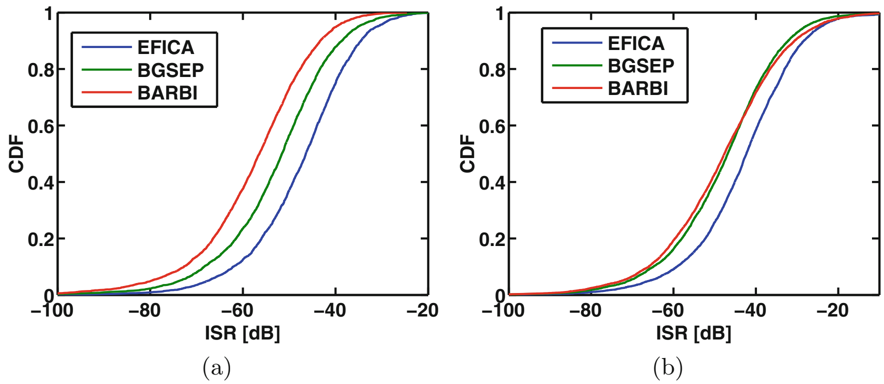

Fig. 2. Cumulative distribution function of ISR of blindly demixed pairs of speech signals: (a) signal length 1 s (16000 samples), (b) signal length: 0.5 s (8000 samples).

3 Adaptive BSS Algorithms

3.1 Scaled Stochastic Natural Gradient Algorithm

Given the current sample of the mixtures $\mathbf{x}_t$ and an estimate of the demixing matrix $\mathbf{W}_t$, the natural gradient updates $\mathbf{W}_t$ as

$$\mathbf{W}_{t+1} = c\left(\mathbf{W}_t + \mu(\mathbf{I} - cf(\mathbf{W}_t\mathbf{x}_t)(\mathbf{W}_t\mathbf{x}_t)^T)\mathbf{W}_t\right),$$

where $f(\ .\ )$ is an appropriately chosen nonlinear function, μ is the step length parameter and c is a scaling parameter

$$c = \frac{N}{\sum_{i,j=1}^{N} |(f(\mathbf{W}_t\mathbf{x}_t)(\mathbf{W}_t\mathbf{x}_t)^T)_{ij}|}.$$

The function $f(\ .\ )$ is applied elementwise. In our simulations, we use the commonly used nonlinear function

$$f(\mathbf{W}_t\mathbf{x}_t) = \tanh(10\mathbf{W}_t\mathbf{x}_t).$$

3.2 Adaptive BGSEP

The adaptive BGSEP algorithm is initialized by an estimate of the demixing matrix $\mathbf{W}_0$ and by M sample covariance matrices computed in the past $M-1$ epochs of the given mixture, each of the length L, as

$$\mathbf{R}_{M-m} = \frac{1}{L}\sum_{\ell=1}^{L} \mathbf{W}_0\mathbf{x}_{\ell-mL}(\mathbf{W}_0\mathbf{x}_{\ell-mL})^T \tag{7}$$

$m = 1, \ldots, M-1$. $\mathbf{R}_M$ is set to zero matrix.

Given a t-th new sample $\mathbf{x}_t$, BGSEP updates the M-th covariance as

$$\mathbf{R}_M = ((s-1)\mathbf{R}_M + \mathbf{W}_t\mathbf{x}_t(\mathbf{W}_s\mathbf{x}_t)^T)/s \tag{8}$$

where $s = \mathrm{rem}(t, L)$ is the remainder in the division of t by L, and the demixing matrix as

$$\mathbf{W}_{t+1} = (\mathbf{I} - \mu\mathbf{B})\,\mathbf{W}_t. \tag{9}$$

Here, $\mathbf{B}$ is matrix with a zero diagonal, such that each pair of non-diagonal elements B_{ij}, B_{ji} is computed separately as a solution to a 2×2 set of linear equations

$$\begin{bmatrix} B_{ij} \\ B_{ji} \end{bmatrix} = \begin{bmatrix} \sum_{m=1}^{M} \frac{r_{jjm}}{r_{iim}} & M \\ M & \sum_{m=1}^{M} \frac{r_{iim}}{r_{jjm}} \end{bmatrix}^{-1} \begin{bmatrix} \sum_{m=1}^{M} \frac{r_{ijm}}{r_{iim}} \\ \sum_{m=1}^{M} \frac{r_{ijm}}{r_{jjm}} \end{bmatrix}, \tag{10}$$

where r_{ijm} is the (i,j)th element of $\mathbf{R}_m$. The update formula (9) was obtained by modifying the off-line BGSEP, see [6,7,18]. The step length parameter μ is chosen so that the estimate varies smoothly while still follows the changes of the demixing matrix. If t equals a multiple of the length of the blocks L, we discard $\mathbf{R}_1$ and set $\mathbf{R}_i \leftarrow \mathbf{R}_{i+1}$ for $i = 1 \ldots M-1$ and $\mathbf{R}_M = \mathbf{0}$, thus resetting the algorithm. Each update of the demixing matrix depends not only on the actual sample of the mixtures but also on previous samples, number of which is given by the block length L and the number of blocks M. Therefore we can expect the increase in L and/or in M will result in the decreased variance of the estimate and increased reaction time for the change in the true mixing matrix and vice versa. The algorithm is summarized in Algorithm 1.

Algorithm 1. Adaptive BGSEP update

```
Input: x_t, W, R_1 ... R_M, t, L;
t = t + 1, s ← rem(t − 1, L) + 1;
R_M ← ((s − 1)R_M + W x_t (W x_t)^T)/s;
Compute elements of B via (10);
W ← (I − μB)W;
if s = L then
    for m = 1 : M − 1 do
        R_m ← R_{m+1};
    end for
    R_M ← 0;
end if
Output: W, R_1 ... R_M, t;
```

3.3 Adaptive BARBI

The online BARBI algorithm works similarly to BGSEP, but in addition to covariances $\mathbf{R}_m$, its initialization requires also a set of symmetrized sample lag one covariances

$$\mathbf{S}_m = \frac{1}{2L}\sum_{\ell=1}^{L}[\mathbf{W}_0\mathbf{x}_{\ell-mL}(\mathbf{W}\mathbf{x}_{\ell-mL-1})^T + \mathbf{W}_0\mathbf{x}_{\ell-mL-1}(\mathbf{W}_0\mathbf{x}_{\ell-mL})^T] \quad (11)$$

for $m = 1 \ldots M-1$, $\mathbf{S}_M = \mathbf{0}$. Given a k-th new sample $\mathbf{x}_k$, BARBI updates the M-th lag one covariance as

$$\mathbf{S}_M = \frac{s-1}{s}\mathbf{S}_M + \frac{\mathbf{W}\mathbf{x}_t(\mathbf{W}\mathbf{x}_{t-1})^T}{2s} + \frac{\mathbf{W}\mathbf{x}_{t-1}(\mathbf{W}\mathbf{x}_t)^T}{2s}.$$

The updates of lag zero covariance and the demixing matrix are the same as in BGSEP, except the equations for the non-diagonal elements of $\mathbf{B}$ take the form

$$\begin{bmatrix} B_{ij} \\ B_{ji} \end{bmatrix} = \begin{bmatrix} \sum_{m=1}^{M} \mathbf{q}_{im}^T \mathbf{p}_{jjm} & M \\ M & \sum_{m=1}^{M} \mathbf{q}_{jm}^T \mathbf{p}_{iim} \end{bmatrix}^{-1} \cdot \begin{bmatrix} \sum_{m=1}^{M} \mathbf{q_{im}}^T \mathbf{p_{ijm}} \\ \sum_{m=1}^{M} \mathbf{q}_{jm}^T \mathbf{p}_{ijm} \end{bmatrix}, \quad (12)$$

where

$$\mathbf{q}_{im} = \frac{1}{r_{iim}(r_{iim}^2 - |s_{iim}|^2)} \begin{bmatrix} r_{iim}^2 + |s_{iim}|^2 \\ -2s_{iim}r_{iim} \end{bmatrix}, \quad (13)$$

$$\mathbf{p}_{ijm} = \begin{bmatrix} r_{ijm} \\ s_{ijm} \end{bmatrix}. \quad (14)$$

Here s_{ijm} is the (i,j)th element of $\mathbf{S}_m$. The update formula (12) was obtained by modifying the off-line BARBI, see [7,18]. After L iterations the algorithm is reset as in BGSEP. The update step of adaptive BARBI is summarized in Algorithm 2.

Algorithm 2. Adaptive BARBI update

Input: $\mathbf{x}_t$, $\mathbf{x}_{t-1}$, $\mathbf{W}$, $\mathbf{R}_1 \ldots \mathbf{R}_M$, $\mathbf{S}_1 \ldots \mathbf{S}_M$, t, L;
$t = t+1$, $s \leftarrow \mathrm{rem}(t-1, L) + 1$;
$\mathbf{R}_M \leftarrow ((s-1)\mathbf{R}_M + \mathbf{W}\mathbf{x}_t(\mathbf{W}\mathbf{x}_t)^T)/s$;
$\mathbf{S}_M \leftarrow ((s-1)\mathbf{S}_M + 1/2(\mathbf{W}\mathbf{x}_t(\mathbf{W}\mathbf{x}_{t-1})^T + \mathbf{W}\mathbf{x}_{t-1}(\mathbf{W}\mathbf{x})^T))/s$;
Compute elements $\mathbf{B}$ via (12);
$\mathbf{W} \leftarrow (\mathbf{I} - \mu\mathbf{B})\mathbf{W}$;
if $s = L$ **then**
  for $m = 1 : M-1$ **do**
    $\mathbf{R}_m \leftarrow \mathbf{R}_{m+1}, \mathbf{S}_m \leftarrow \mathbf{S}_{m+1}$;
  end for
  $\mathbf{R}_M \leftarrow \mathbf{0}$, $\mathbf{S}_M \leftarrow \mathbf{0}$;
end if
Output: $\mathbf{W}$, $\mathbf{R}_1 \ldots \mathbf{R}_M$, $\mathbf{S}_1 \ldots \mathbf{S}_M$, t, L;

4 Experiments

We examine tracking properties of the natural gradient, adaptive BGSEP and adaptive BARBI in the following example. Consider a pair of natural speech signals taken from the same database as in Sect. 2. We mix them by the mixing matrix $\mathbf{A}_1 = \begin{bmatrix} 1 & 2 \\ 2 & -1 \end{bmatrix}$, and change it abruptly to another matrix $\mathbf{A}_2 = \begin{bmatrix} -1 & 2 \\ 2 & 1 \end{bmatrix}$ at time instant $t = 4.1875$ s. For NG the step length parameter μ was set to 0.001. For BGSEP the block length was set to $L = 200$ samples, the number of blocks was set to $M = 10$, and the step length parameter was set $\mu_{bg} = 0.01$. The parameters were manually selected as such that the methods yield best performances. For adaptive BARBI we have chosen the same block length and the same number of blocks, and the step length $\mu_{barbi} = 0.001$. The ability of the algorithms to adapt to the change of the mixing matrix is studied in terms of the estimated gain matrix $\mathbf{G}_t = \widehat{\mathbf{W}}_t \mathbf{A}_t$, where $\mathbf{A}_t$ is the mixing matrix at time t and $\widehat{\mathbf{W}}_t$ is the estimated demixing matrix. In the ideal case, $\mathbf{G}_t$ should be a diagonal or counter-diagonal matrix. The results for all three algorithms are plotted in Fig. 3. Gain matrices for all three algorithms switch from near diagonal to near counter-diagonal following the abrupt change of the true mixing matrix.

Next, we have computed the instantaneous interference to signal ratio ISR of the separated signals in moving time window of the length of 10000 samples (0.625 s). The results are plotted in Fig. 4. The BGSEP achieves the same separation as NG in the first half of the signal, attaining average ISR of −32.84 dB and −33.41 dB respectively, both outperforming BARBI with −27.13 dB. In the

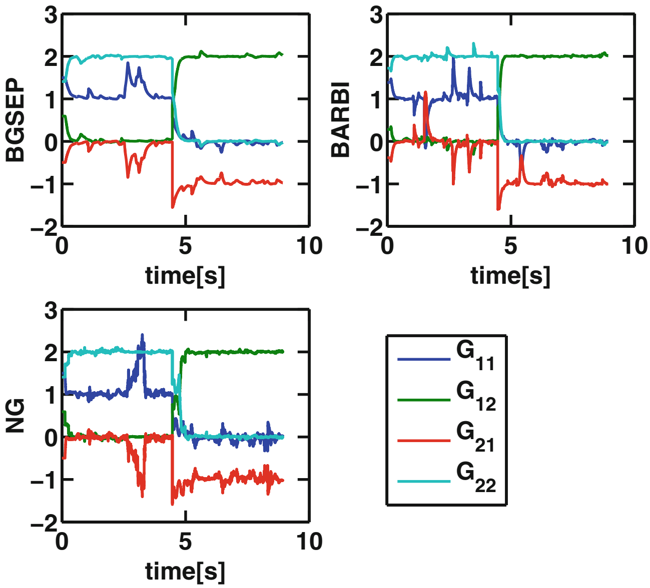

Fig. 3. Evolution of the elements of the gain matrix **G** for BGSEP, BARBI and NG algorithms in the case of an abrupt change in the mixing matrix. The gain matrices switch between diagonal and counterdiagonal in reaction to the change in the true mixing matrix.

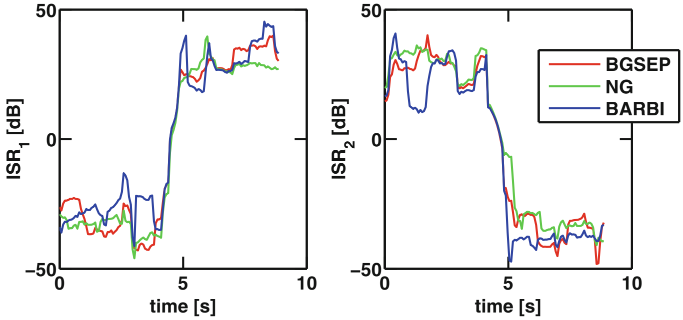

Fig. 4. Instantaneous SIR for BGSEP, NG and BARBI algorithms in the case of an abrupt change in the mixing matrix.

second half of the signal, BARBI attains the lowest average ISR of −38.17 dB, BGSEP being second best with −35.51 dB and NG achieving −33.09 dB.

5 Conclusion

We have proposed two novel adaptive algorithms for the blind separation and compare their performance with those of the natural gradient technique. The proposed techniques achieve separation better or comparable to that of natural gradient algorithm. The next step will be an application of these methods in frequency domain BSS algorithms and a comparison with adaptive time domain BSS [19].

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