Blind Separation of Nonstationary Markovian Sources Using an Equivariant Newton–Raphson Algorithm

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***Abstract*—This letter presents a new maximum likelihood method for blindly separating linear instantaneous source mixtures, where source signals are assumed to be mutually independent, Markovian and possibly nonstationary. The proposed approach first extends previous works, by Hosseini *et al.* to possibly nonstationary sources using two approaches based on blocking and kernel smoothing, respectively. Moreover, to reduce time consumption, we propose an equivariant modified Newton–Raphson algorithm to solve the estimating equations, and we introduce polynomial estimators for the conditional score functions used in our method. Experimental results, both for artificial and real (speech) signals, prove the better performance of our method as compared to various classical blind separation algorithms.**

***Index Terms*—Blind source separation (BSS), Markovian model, Newton–Raphson algorithm, nonstationary sources, polynomial score function estimator.**

I. Introduction

In linear instantaneous Blind Source Separation (BSS), we aim at recovering some unknown source signals from a set of observed linear combinations of these sources. Assuming N samples of K observations resulting from the mixture of K unknown sources, we denote, respectively, $\mathbf{x}(t) = [x_1(t), \ldots, x_K(t)]^T$ and $\mathbf{s}(t) = [s_1(t), \ldots, s_K(t)]^T$ the observation and source vectors. The linear instantaneous mixture model, in a noiseless context, is hence defined by

$$\mathbf{x}(t) = \mathbf{A}\mathbf{s}(t) \quad t = 1, \ldots, N \tag{1}$$

where $\mathbf{A}$ is an unknown $K \times K$ mixing matrix. Given this model, the aim of BSS methods is to find an estimate $\hat{\mathbf{A}}$ of the matrix $\mathbf{A}$, up to permutation and scale indeterminacies, in order to then estimate the sources as $\hat{\mathbf{A}}^{-1}\mathbf{x}$.

To solve this problem, one of the most commonly used approaches is the Independent Component Analysis (ICA), where one achieves separation by assuming the mutual independence of the sources. To obtain independent signals, three different features may be exploited: non-Gaussianity, autocorrelation or nonstationarity of the sources [1].

In [2], Hosseini *et al.* proposed a Maximum Likelihood (ML) BSS approach where sources were modeled as q-th order stationary Markovian processes. The Markovian assumption helped to improve separation performance by taking into account the temporal autocorrelation of the sources.

Nevertheless, this method suffers from a high computational cost, which is due to a cumbersome nonparametric estimation of the score functions and to slow convergence of the gradient algorithm used for solving the estimating equations. Moreover, it is based on the source stationarity assumption, which is obviously unrealistic for most real signals.

Starting from this idea, we propose in this letter an ML Markovian method, where we exploit possible source nonstationarity by adapting two approaches based on blocking and kernel smoothing, respectively. This method can take into account higher-order nonstationarities, contrary to most classical nonstationary BSS algorithms. Furthermore, we propose a modified equivariant Newton–Raphson algorithm to solve estimating equations and define 3rd-order polynomial Least Mean Square (LMS) estimators for the conditional score functions.

II. Markovian BSS Method Using Equivariant Newton–Raphson Algorithm

Assuming the mixture model (1), we want to estimate a separating matrix $\mathbf{B} = \mathbf{A}^{-1}$ up to a permutation and a diagonal matrix. In an ML approach, this is done by maximizing, with respect to the matrix $\mathbf{B}$, the joint pdf of all the samples of all the components of the observation vector $\mathbf{x}$, defined by

$$f_{\mathbf{x}}(x_1(1), \ldots, x_K(1), \ldots\ldots, x_1(N), \ldots, x_K(N)). \tag{2}$$

Assuming the sources are mutually independent and obey a q-th order Markovian model[1], then using the Bayes rule and simplifying the source conditional pdfs as in [2], we can rewrite (2) as

$$\left(\frac{1}{|\det(\mathbf{B}^{-1})|}\right)^N \prod_{i=1}^{K} \Bigg[f_{s_i}(s_i(1), \ldots, s_i(q)) \times \prod_{t=q+1}^{N} f_{s_i(t)}(s_i(t) \,|\, s_i(t-1), \ldots, s_i(t-q)) \Bigg] \tag{3}$$

where f_{s_i} is the joint pdf of the q first samples of each source s_i and $f_{s_i(t)}$ is the conditional pdf of source s_i, at time t.

By maximizing the logarithm of (3), following the same steps as in [2], we finally obtain the following set of $K(K-1)$ estimating equations

$$E_{N-q}\left[\sum_{l=0}^{q} \psi_{s_i(t)}^{l}(s_i(t)|s_i(t-1), \ldots,\ s_i(t-q))s_j(t-l)\right] = 0, \quad i \neq j = 1, \ldots, K \tag{4}$$

[1]The Markovian model can take into account the nonlinear temporal autocorrelation between the signal samples, which is not the case when using ARMA models, for example.

Manuscript received September 24, 2008; revised December 10, 2008. Current version published April 07, 2009. The associate editor coordinating the review of this manuscript and approving it for publication was Dr. Alfred Mertins.

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Digital Object Identifier 10.1109/LSP.2009.2016448

where $E_{N-q}[\cdot] = (1)/(N-q)\sum_{t=q+1}^{N}$ represents the temporal mean over $(N-q)$ samples and $\psi^l_{s_i(t)}(\cdot)$ is the conditional score function of source s_i at time t with respect to source sample $s_i(t-l)$, defined as

$$\psi^l_{s_i(t)}(s_i(t)|s_i(t-1),\ldots,s_i(t-q)) = \frac{-\partial \log f_{s_i(t)}(s_i(t)\,|\,s_i(t-1),\ldots,s_i(t-q))}{\partial s_i(t-l)}, \quad \forall \quad 0 \leq l \leq q.$$

Contrary to [2], where a gradient ascent scheme is used to solve (4), we propose to use a faster approach based on a modified version of the Newton–Raphson algorithm. Thus, we modify the step size of the classical Newton–Raphson algorithm so that the new estimate of the separating matrix $\hat{\mathbf{B}}$ is proportional to the previous value $\tilde{\mathbf{B}}$ of this matrix, following the formula $\hat{\mathbf{B}} = (\mathbf{I}+\boldsymbol{\Delta})\tilde{\mathbf{B}}$, where $\mathbf{I}$ is the identity matrix. This formulation has the advantage of ensuring the equivariance property of the algorithm [3]. Indeed, post-multiplying the above updating formula by the mixing matrix $\mathbf{A}$, one can easily prove that the global mixing-unmixing matrix only depends on its initial value.

In the following, we restrict our calculus to the case $K=2$ for simplicity. The extension of the results to a higher number of sources is straightforward. Post-multiplying the updating formula by the observation vector $\mathbf{x}$, the new source estimate $\hat{\mathbf{s}} = \hat{\mathbf{B}}\mathbf{x}$ can be written as a function of its previous value $\tilde{\mathbf{s}} = \tilde{\mathbf{B}}\mathbf{x}$, according to $\hat{\mathbf{s}} = (\mathbf{I}+\boldsymbol{\Delta})\tilde{\mathbf{s}}$. The new estimate $\hat{\mathbf{B}}$ is equal to the actual separating matrix if $\hat{\mathbf{s}}$ satisfies (4). We denote $\boldsymbol{\Delta} = \begin{pmatrix}\delta_{11} & \delta_{12}\\ \delta_{21} & \delta_{22}\end{pmatrix}$. The diagonal entries of $\boldsymbol{\Delta}$ may be set to any arbitrary value due to the scaling indeterminacy of ICA. The off-diagonal terms δ_{12} and δ_{21} are computed as follows. Using a first-order Taylor expansion of the score function $\psi^l_{s_i(t)}$ at the current value $\tilde{s}_i(t)$, we obtain after some simplifications the following linear set of two equations with two unknowns δ_{12} and δ_{21} [4]

$$\begin{aligned}
&E_{N-q}\left[\sum_{l=0}^{q}\psi^l_{s_i(t)}(\tilde{s}_i(t)\,|\,\tilde{s}_i(t-1),..,\ \tilde{s}_i(t-q)).\tilde{s}_i(t-l)\right]\delta_{ji}\\
&\quad + E_{N-q}\left[\sum_{l=0}^{q}\left\{\sum_{n=0}^{q}\frac{\partial\psi^l_{s_i(t)}}{\partial s_i(t-n)}\right.\right.\\
&\left.\left.(\tilde{s}_i(t)\,|\,\tilde{s}_i(t-1),\ldots,\ \tilde{s}_i(t-q))\tilde{s}_j(t-n)\right\}\cdot\tilde{s}_j(t-l)\right]\delta_{ij}\\
&\quad = -E_{N-q}\left[\sum_{l=0}^{q}\psi^l_{s_i(t)}(\tilde{s}_i(t)\,|\,\tilde{s}_i(t-1),\ldots,\right.\\
&\qquad\left.\tilde{s}_i(t-q))\cdot\tilde{s}_j(t-l)\right], \qquad i\neq j=1,2. \qquad (5)
\end{aligned}$$

To compute the coefficients of (5), we need the score functions $\psi^l_{s_i(t)}$ and their derivatives. Since the sources s_i are unknown, in practice their score functions may be estimated only via the reconstructed sources $\hat{\mathbf{s}}(t) = \hat{\mathbf{B}}\mathbf{x}(t)$, computed at each iteration of the Newton–Raphson algorithm. This approximation may be obviously inaccurate at the first iterations of the algorithm, but it does not usually degrade the convergence towards actual sources. In [2], third-order cardinal spline kernels are used to compute the estimated conditional score functions of the sources, $\psi^l_{\hat{s}_i(t)}$. This method is quite accurate but is very time consuming, and computing score function derivatives in this case is a difficult task. In the following, we propose a simpler estimator of the score functions based on a polynomial LMS estimator. Furthermore, we adapt this method to handle possible source nonstationarity.

III. Nonstationary Polynomial Estimation of the Score Functions

A. Polynomial LMS Estimator

In the following, we want to find parametric LMS estimators for the conditional score functions required to solve (5). First, each conditional score function may be written as

$$\psi^l_{\hat{s}_i(t)}(\hat{s}_i(t)\,|\,\hat{s}_i(t-1),\ldots,\hat{s}_i(t-q)) = \psi^l_{\hat{s}_i(t)}(\hat{s}_i(t),\ldots,\hat{s}_i(t-q)) - \psi^l_{\hat{s}_i(t)}(\hat{s}_i(t-1),\ldots,\hat{s}_i(t-q)). \quad (6)$$

Our aim is to estimate each of the joint score functions in the right-hand term of (6) using two parametric LMS estimators $g^l_{\hat{s}_i(t)}(\hat{s}_i(t),\ldots,\hat{s}_i(t-q),\mathbf{W})$ and $u^l_{\hat{s}_i(t)}(\hat{s}_i(t-1),\ldots,\hat{s}_i(t-q),\mathbf{V})$, respectively. Thus, we have for the first estimator

$$\mathbf{W}^l_{\text{LMS}}(\hat{s}_i(t)) = \arg\min_{\mathbf{W}} E\{[\psi^l_{\hat{s}_i(t)}(\hat{s}_i(t),\ldots,\hat{s}_i(t-q)) - g^l_{\hat{s}_i(t)}(\hat{s}_i(t),\ldots,\hat{s}_i(t-q),\mathbf{W})]^2\}. \quad (7)$$

Using theoretical results in [5], one can prove that the above estimator satisfies

$$\begin{aligned}
\mathbf{W}^l_{\text{LMS}}(\hat{s}_i(t)) &= \arg\min_{\mathbf{W}}\left\{E\left[\left(g^l_{\hat{s}_i(t)}(\hat{s}_i(t),\ldots,\quad\hat{s}_i(t-q),\mathbf{W})\right)^2\right]\right.\\
&\quad\left.-2E\left[\frac{\partial g^l_{\hat{s}_i(t)}(\hat{s}_i(t),\ldots,\hat{s}_i(t-q),\mathbf{W})}{\partial\hat{s}_i(t-l)}\right]\right\}. \quad (8)
\end{aligned}$$

The parametric function $g^l_{\hat{s}_i(t)}(\hat{s}_i(t),\ldots,\hat{s}_i(t-q),\mathbf{W})$ may be defined in different ways, but should be easily differentiable to enable fast estimation of the score function derivatives. Therefore, we choose to use polynomial functions, which are especially attractive for their simplicity and their linearity with respect to the parameters. We first write the polynomial function $g^l_{\hat{s}_i(t)}(\hat{s}_i(t),\ldots,\hat{s}_i(t-q),\mathbf{W})$ as

$$\begin{aligned}
g^l_{\hat{s}_i(t)}(\hat{s}_i(t),\ldots,\hat{s}_i(t-q),\mathbf{W}) &= \sum_j w^l_j(\hat{s}_i(t))h_j(\hat{s}_i(t),\ldots,\hat{s}_i(t-q))\\
&= \mathbf{h}^T\mathbf{W}^l(\hat{s}_i(t)) \qquad (9)
\end{aligned}$$

where $h_j(\hat{s}_i(t),\ldots,\hat{s}_i(t-q))$ and $w^l_j(\hat{s}_i(t))$ are respectively the monomial functions and the coefficients. Replacing $g^l_{\hat{s}_i(t)}(\cdot)$ in (8) by its polynomial expression, then setting to zero the derivative of the function to be minimized, one finally obtains the following parameters $\mathbf{W}^l_{\text{LMS}}(\hat{s}_i(t))$, $\forall l=0,\ldots,q$, which minimize the mean square error of the estimator

$$\mathbf{W}^l_{\text{LMS}}(\hat{s}_i(t)) = (E[\mathbf{h}\mathbf{h}^T])^{-1}E\left[\frac{\partial\mathbf{h}}{\partial\hat{s}_i(t-l)}\right]. \quad (10)$$

The parameters of the LMS Polynomial estimator $u^l_{\hat{s}_i(t)}(\hat{s}_i(t-1),\ldots,\hat{s}_i(t-q),\mathbf{V})$ of the second joint score function, denoted by $\mathbf{V}^l_{\text{LMS}}(\hat{s}_i(t))$, can be obtained in a similar manner.

The orders of the polynomials are chosen to ensure accurate estimates in a reasonable running time. Thus, after some tests, the two polynomial functions were chosen to be

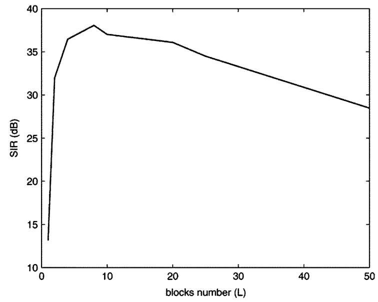

Fig. 1. Mean SIR as a function of L.

third-order polynomials, which respectively contain all possible terms in $\{1, (\hat{s}_i(t), \ldots, \hat{s}_i(t-q)), (\hat{s}_i(t), \ldots, \hat{s}_i(t-q))^2, (\hat{s}_i(t), \ldots, \hat{s}_i(t-q))^3\}$ and $\{1, (\hat{s}_i(t-1), \ldots, \hat{s}_i(t-q)), (\hat{s}_i(t-1), \ldots, \hat{s}_i(t-q))^2, (\hat{s}_i(t-1), \ldots, \hat{s}_i(t-q))^3\}$.[2]

B. Nonstationary Estimation of the Score Functions

The estimations of the coefficients $\mathbf{W}^l_{\text{LMS}}(\hat{s}_i(t))$ and $\mathbf{V}^l_{\text{LMS}}(\hat{s}_i(t))$ require the computation of the expectations in (10) and in the corresponding equation for $\mathbf{V}^l_{\text{LMS}}(\hat{s}_i(t))$. Nevertheless, this is not possible unless we make some statistical assumptions about the sources. To adapt our method to realistic sources, we here propose two formulations that take into account the possible nonstationarity of the source signals by locally estimating the score functions[3]. To this end, the two approaches, first proposed in [6] for nonstationary *uncorrelated* sources, are here adapted to our Markovian nonstationary Newton–Raphson algorithm.

1) Blocking Method: In a blocking approach, the signal, of length N, is split into L adjacent subintervals $I_j, j = 1, \ldots, L$. Under slow variation hypothesis, score functions are supposed to be constant within each of the subintervals I_j. Thus, in each I_j, the score functions do not depend on time, and expectations in (10) are simply replaced by sample means. For instance, taking the same length τ for all sub-intervals, the first set of coefficients $\mathbf{W}^l_{\text{LMS}}(\hat{s}_i(I_j))$ associated to I_j is computed by

$$\mathbf{W}^l_{\text{LMS}}(\hat{s}_i(I_j)) = \left(\frac{1}{\tau - q}\sum_{t=t_1}^{t_2}[\mathbf{h}\mathbf{h}^T]\right)^{-1} \times \frac{1}{\tau - q}\sum_{t=t_1}^{t_2}\left[\frac{\partial \mathbf{h}}{\partial \hat{s}_i(t-l)}\right], \forall l = 0, \ldots, q \quad (11)$$

where $t_1 = (j-1)\tau + q + 1$ and $t_2 = j\tau$.

2) Kernel Smoothing Method: In the above blocking approach, we simply assign the same weight to all samples within a subinterval I_j. This approach is practical but only offers limited choices for the weighting window. A more natural idea is to define a sequence of locally varying coefficients which adjust the weighting around the time point of interest to the smoothness of the signal. Indeed, a common method is to describe these weights using a kernel function with a chosen window width adapted to the data. For instance, we here propose to use the classical Nadaraya-Watson estimator [7] to estimate the expectations in (10). Thus, if we denote these expectations as $E_\phi = E[\phi(x_i(t), x_i(t-1) \ldots, x_i(t-q))]$ where $\phi(\cdot)$ is a general notation for the nonlinear functions in (10), our estimator may be defined as

$$\hat{E}_\phi = \frac{\sum_{\tau=q+1}^{N} \kappa\left(\frac{\tau - t}{\nu}\right)\phi(x_i(\tau), \ldots, x_i(\tau - q))}{\sum_{\tau=q+1}^{N} \kappa\left(\frac{\tau - t}{\nu}\right)} \quad (12)$$

where $\kappa(\cdot)$ is a kernel function and ν the weighting window width. This estimator should be more accurate than the blocking algorithm, but it is unfortunately very time consuming, especially when signals are large-sized. To reduce the time consumption, we can take a sparser estimation such as

$$\hat{E}_\phi = \frac{\sum_{l=l_1}^{L} \kappa\left(\frac{\frac{lN}{L} - t}{\nu}\right)\phi\left(x_i\left(\frac{lN}{L}\right), \ldots, x_i\left(\frac{lN}{L} - q\right)\right)}{\sum_{l=l_1}^{L} \kappa\left(\frac{\frac{lN}{L} - t}{\nu}\right)}$$

where $(l_1 N)/(L)$ is the first integer greater than q and L is chosen so that $(lN)/(L)$ is an integer, $\forall l \in [l_1, L]$.

IV. Experiments With Artificial and Real Data

A. Artificial Signals

For each of the following experiments, the estimated sources, $\hat{s}_i$, are normalized to have the same variances and signs as the sources, s_i. The output Signal to Interference Ratio (in dB) is computed by $\text{SIR} = (1)/(K)\sum_{i=1}^{K} 10\log_{10}(E[s_i^2])/(E[(\hat{s}_i - s_i)^2])$, where K is the number of sources.

In the first experiment, we want to highlight the relevance of taking into account the possible nonstationarity of the signals in BSS problems. Therefore, we compare our nonstationary blocking Markovian method to the simple case when the nonstationary sources are supposed to be stationary.

First, we generate two independent, white and uniformly distributed signals $e_1(t)$ and $e_2(t)$, that we filter by, respectively, two autoregressive (AR) filters in order to obtain two 1st-order Markovian sources following the scheme $\varsigma_i(t) = e_i(t) + \rho_i \varsigma_i(t-1)$. The chosen coefficients are $\rho_1 = 0.2$ and $\rho_2 = 0.9$. Finally, we split the signals $\varsigma_i(t)$ into 8 subintervals, then multiply each block by a different coefficient $\alpha_p, p = 1, \ldots, 8$ to obtain the nonstationary source signals s_i. The mixture is artificially obtained using the mixing matrix $\mathbf{A} = \begin{pmatrix} 1 & 0.99 \\ 0.99 & 1 \end{pmatrix}$. To perform separation, we apply our blocking Markovian method for different values of the number L of blocks, then we compute the average SIR over 100 Monte Carlo simulations. For each simulation, we randomly generate the signals $e_1(t)$ and $e_2(t)$. The results obtained for $N = 1000$ source samples are shown in Fig. 1 as a function of L.

The case $L = 1$ corresponds to the stationary version of our Markovian algorithm, and only yields 13-dB mean SIR. Fig. 1 shows that our nonstationary algorithm outperforms the stationary one, whatever the number L. The best performance is obtained when $L = 8$, with an average SIR of 37 dB and a standard deviation equal to 7 dB. Note that the algorithm performance is not considerably degraded by overblocking, unless we do not have enough samples in each block to accurately estimate score functions. Indeed, we still obtain more than 35-dB SIRs provided $L < 20$.

In the second step of our experiments, we want to confirm the advantage of taking into account both autocorrelation and nonstationarity in comparison to Pham's nonstationary BSS method [6] which neglects the autocorrelation. Thus, we generate in the

[2]Using for example a first-order Markovian model, i.e., $q = 1$, $\mathbf{h}$ is the vector $[1, \hat{s}_i(t), \hat{s}_i(t-1), \hat{s}_i(t)^2, \hat{s}_i(t-1)^2, \hat{s}_i(t)\hat{s}_i(t-1), \hat{s}_i(t)^3, \hat{s}_i(t-1)^3, \hat{s}_i(t)^2\hat{s}_i(t-1), \hat{s}_i(t)\hat{s}_i(t-1)^2]^T$.

[3]Taking into account the nonstationarity improves the BSS performance and makes it possible even for Gaussian, temporally uncorrelated sources [1].

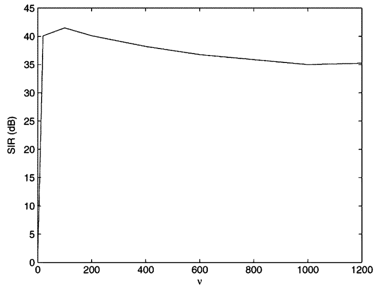

Fig. 2. Mean SIR as a function of the Gaussian kernel window width.

same way as in the first simulation two artificial AR independent 20000-sample signals. The two filter coefficients, ρ_1 and ρ_2, are chosen to be equal to 0.9 in order to create, within each signal, strong temporal autocorrelations which cannot be neglected. These filtered signals are then split into 4 blocks, and each block is multiplied by a different coefficient to generate variance nonstationarity. The resulting source signals, s_i, are then mixed by the same matrix $\mathbf{A}$ as in the previous experiment.

To separate the obtained mixture, we respectively apply our blocking Markovian method and the nonstationary non-Gaussian algorithm proposed by Pham [6]. For each method, we compute the mean SIR over 100 Monte Carlo simulations as a function of L. Our method leads to more than 51-dB mean SIR for $L \in [4\ 500]$. On the contrary, Pham's algorithm leads at best to an SIR of 41 dB.

In the last simulation, we want to verify the advantage of the kernel smoothing method in cases when the blocking method cannot perfectly adapt to the signal statistics. Thus, we generate two independent 1000-sample AR signals. The resulting Markovian signals are split into 200 blocks, and each block is then multiplied by a different coefficient α_p to obtain the sources s_i. Note that, in this case, each stationary block only contains 5 samples, which is clearly not enough to estimate score functions. The generated sources are finally mixed by $\mathbf{A} = \begin{pmatrix} 1 & 0.99 \\ 0.99 & 1 \end{pmatrix}$ and separation is performed using, respectively, our blocking method with different number of blocks L, and our kernel smoothing approach with a Gaussian kernel and a varying window width ν. The mean SIR over 100 Monte Carlo simulations using the kernel method is shown in Fig. 2 versus ν. The best performance is obtained for $\nu = 100$, with an average SIR of 41 dB, whereas the blocking method leads at best to 35 dB in this case. To have enough samples in each block for the estimation of the score functions, the signals should be underblocked, i.e., $L < 200$. Nevertheless, the blocking algorithm is dramatically faster than the kernel smoothing approach, especially with long signals: using for instance two 1000-sample nonstationary Markovian signals with 8 blocks, the running times for each iteration on a 1.53 GHz AMD-Athlon PC with 500 MB of memory were 0.2 and 25 seconds using the blocking and the kernel algorithms, respectively. Therefore, in the following, we only use the blocking algorithm to perform the separation of real speech signals with very large number of samples.

B. Simulations With Speech Signals

Using the same mixture matrix $\mathbf{A}$ as in the previous Subsection, we first generate ten couples of mixed 100 000-sample speech signals. The mean of the SIRs for these ten couples is computed using respectively our nonstationary Markovian method and 19 standard algorithms available in the ICALAB Toolbox [8]. Note that this Toolbox includes for example the SONS algorithm, which is a second-order approach taking into account both nonstationarity and temporal autocorrelation of the signals. In a second step, we apply our blocking method and the above 19 algorithms to separate an artificial linear instantaneous mixture of eight 100 000-sample speech signals. The best results obtained for both tests are summarized in Table I.

TABLE I
BEST SIRs OBTAINED BY THE BLOCKING MARKOVIAN ALGORITHM AND THE 19 ICALAB ALGORITHMS FOR THE SEPARATION OF TEN COUPLES OF MIXED SPEECH SIGNALS AND A MIXTURE OF EIGHT SPEECH SIGNALS

Source signals	best mean of SIRs (dB)	
	blocking algorithm	ICALAB algorithms
Speech couples	91	58
8 speech signals	66	36

V. CONCLUSION

We presented a new blind Markovian source separation method which simultaneously takes advantage of the non-Gaussianity, nonstationarity and autocorrelation of the source signals. The computational cost is highly reduced thanks to an efficient modified Newton–Raphson algorithm and a simple polynomial estimator for conditional score functions and their derivatives. Our simulations confirmed the relevance of our approach when compared to methods which neglect either nonstationarity or autocorrelation of the signals. Moreover, the results obtained with speech signals clearly prove the better performance of our method with respect to all classical algorithms of the ICALAB Toolbox. Applications of this method in realistic mixture context, especially for one-dimensional astrophysical signals, will be presented in future works.

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