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On joint diagonalization of cumulant matrices for independent component analysis of MRS and EEG signals

Laurent Albera, Amar Kachenoura, Fabrice Wendling, Lotfi Senhadji and Isabelle Merlet

***Abstract*— An extension of the original implementation of JADE, named eJADE$^{(1)}$ hereafter, was proposed in 2001 to perform independent component analysis for any combination of statistical orders greater than or equal to three. More precisely, eJADE$^{(1)}$ relies on the joint diagonalization of a set of several cumulant matrices corresponding to different matrix slices of one or several higher order cumulant tensors. An efficient way, without lose of statistical information, of reducing the number of third and fourth order cumulant matrices to be jointly diagonalized is proposed in this paper. The resulting approach, named eJADE$^{(2)}_{3,4}$, can be interpreted as an improvement of the eJADE$^{(1)}_{3,4}$ method. A performance comparison with classical methods is conducted in the context of MRS and EEG signals showing the good behavior of our technique.**

I. Introduction

Independent Component Analysis (ICA) has lately raised great interest in numerous applications including telecommunications, audio, or biomedical engineering [1], [9]–[11], [17], [19]. For instance, Hu et al. [9] proposed to use ICA for identification and removal of the reference signal contribution from intracranial ElectroEncephaloGraphy (EEG) recorded with a scalp reference signal. They showed that such an approach gave better results than bipolar or average common reference EEG montages. In fact ICA aims at extracting the sources i) based on their mutual independence and ii) from the sole observation of the mixtures recorded by electrodes.

Comon originally proposed to maximize contrast functions (simply called contrasts) derived from Higher Order (HO) cumulants of the data in order to perform ICA [5]. This led to the famous CoM2 method using Fourth Order (FO) cumulants. Another famous ICA technique method appeared at the same period, proposed by Cardoso and Souloumiac [3]. The latter, named JADE$^{(1)}_4$ hereafter, maximizes a novel FO contrast by means of the joint diagonalization of a set of several cumulant matrices corresponding to different matrix slices of the FO cumulant tensor. A second implementation, called JADE$^{(2)}_4$ hereafter, was also given aiming at reducing the number of matrices to be jointly diagonalized without loss of statistical information. This requires to compute the principal eigenvectors of the symmetric square unfolding matrix, named quadricovariance, of the whole FO cumulant tensor. The idea of combining HO cumulants of different orders was originally proposed by Moreau [15]. Moreau unified both contrasts maximized by CoM2 and JADE$_4$, respectively, through a more general contrast. Then he extended it to any HO statistics and gave the possibility of combining different HO's. Moreover, he showed how such a generalized contrast could be maximized by using a Jacobi-like procedure similar to that used in CoM2. In addition, he showed that a link with joint diagonalization of a set $\mathcal{N}$ of cumulant matrices corresponding to different matrix slices of one or several HO cumulant tensors can be established for some values of his generalized contrast. In particular, such a link allowed him to propose an extension of JADE$^{(1)}_4$, called eJADE$^{(1)}$ hereafter, to any HO('s). More recently, Blaschke and Wiskott proposed to maximize a contrast combining Third Order (TO) and FO cumulants leading to the CubICA technique [2]. If CubICA can be seen as an extension of CoM2, the contrast maximized by authors is just a particular case of the general contrast introduced by Moreau [15]. The optimization scheme is close enough to that proposed by Moreau. Hence the response made by Moreau two years later [16].

The solution proposed in this paper, named eJADE$^{(2)}_{3,4}$, aims at improving the eJADE$^{(1)}_{3,4}$ method [15]. More precisely, an efficient way, without lose of statistical information, of reducing the number of TO and FO cumulant matrices to be jointly diagonalized is proposed. A performance comparison with nine classical ICA methods is performed in the context of Magnetic Resonance Spectroscopic (MRS) and EEG signals showing the good behavior of our technique.

II. Assumptions and problem formulation

We assume that K realizations of an N-dimensional real random vector $\boldsymbol{x}$ are observed such that:

$$\boldsymbol{x} = \textstyle\sum_{p=1}^{P} \boldsymbol{a}_p\, s_p + \boldsymbol{\nu} = \boldsymbol{A}\,\boldsymbol{s} + \boldsymbol{\nu} \qquad (1)$$

where $\boldsymbol{s} = [s_1, \cdots, s_P]^{\mathsf{T}}$ is a P-dimensional real random vector, called source vector, with mutually independent components. We also assume that each source s_p has a non-zero TO or FO marginal cumulant. Matrix $\boldsymbol{A} = [\boldsymbol{a}_1, \cdots, \boldsymbol{a}_P]$ is the $(N \times P)$ static mixing matrix with linearly independent columns $\boldsymbol{a}_p$. As far as the N-dimensional real random vector $\boldsymbol{\nu}$ is concerned, it represents an additive Gaussian noise independent of the source vector.

The goal of ICA is to determine a separating matrix, $\boldsymbol{W}$, such that:

$$\boldsymbol{y} = \boldsymbol{W}^{\mathsf{T}}\,\boldsymbol{x} \qquad (2)$$

is an estimate of vector $\boldsymbol{s}$ up to a multiplicative *trivial* matrix (i.e. of the form $\boldsymbol{\Lambda\Pi}$ where $\boldsymbol{\Lambda}$ is invertible diagonal and $\boldsymbol{\Pi}$ is a permutation). In eJADE$^{(2)}_{3,4}$, as in numerous other ICA algorithms, the construction of $\boldsymbol{W}$ requires the blind identification of mixture $\boldsymbol{A}$.

L. Albera, A. Kachenoura, F. Wendling, L. Senhadji and I. Merlet are with the INSERM U642, Rennes F-35000, France, and the Université de Rennes 1, LTSI, Rennes F-35000, France.

III. The core of the eJADE$^{(2)}_{3,4}$ method

As most of ICA techniques, eJADE$^{(2)}_{3,4}$ requires a prewhitening step. Such a procedure is well described in [5, section 2.2] and it is not detailed hereafter. Just recall that it allows to reduce the search space to the set of the orthogonal mixing matrices. As a result, without loss of generality, consider that $\boldsymbol{x}$ and $\boldsymbol{A}$ given in (1) are a P-dimensional random vector and a $(P\times P)$ orthogonal matrix, respectively.

A. Toward an extended HO statistical matrix

Let $\mathcal{C}_{n_1,n_2,n_3,\boldsymbol{x}}$ and $\mathcal{C}_{n_1,n_2,n_3,n_4,\boldsymbol{x}}$ be the entries of the TO and FO cumulant arrays, $\boldsymbol{\mathcal{C}}_{3,\boldsymbol{x}}$ and $\boldsymbol{\mathcal{C}}_{4,\boldsymbol{x}}$, respectively, of the observation vector $\boldsymbol{x}$ (1). They can be sorted together in a $(M\times P^2)$ rectangular matrix $\boldsymbol{T}_{\boldsymbol{x}}^{(3,4)}$ where $M=P+P^2$, entrywise defined by $T^{(3,4)}_{m_1,m_2,\boldsymbol{x}}=\mathcal{C}_{p_1,p_2,m_1,\boldsymbol{x}}$ where $m_2=p_2+P(p_1-1)$ for $m_1\leq P$ and $T^{(3,4)}_{m_1,m_2,\boldsymbol{x}}=\mathcal{C}_{p_1,p_2,p_3,p_4,\boldsymbol{x}}$ where $m_1=p_4+Pp_3$ and $m_2=p_2+P(p_1-1)$ for $m_1>P$. Under assumptions of section II and using the multi-linearity property enjoyed by cumulants, we can show that matrix $\boldsymbol{T}_{\boldsymbol{x}}^{(3,4)}$ has the following algebraic structure:

$$\boldsymbol{T}_{\boldsymbol{x}}^{(3,4)}=\boldsymbol{C}(\boldsymbol{A}\oslash\boldsymbol{A})^{\mathsf{T}} \tag{3}$$

where the $(M\times P)$ matrix $\boldsymbol{C}=[\boldsymbol{C}_{3,\boldsymbol{s}}\boldsymbol{A}^{\mathsf{T}},\boldsymbol{C}_{4,\boldsymbol{s}}(\boldsymbol{A}\oslash\boldsymbol{A})^{\mathsf{T}}]^{\mathsf{T}}$ is function of the $(P\times P)$ following diagonal matrices $\boldsymbol{C}_{3,\boldsymbol{s}}=\mathrm{diag}\left([\mathcal{C}_{1,1,1,\boldsymbol{s}},\mathcal{C}_{2,2,2,\boldsymbol{s}},\cdots,\mathcal{C}_{P,P,P,\boldsymbol{s}}]\right)$ and $\boldsymbol{C}_{4,\boldsymbol{s}}=\mathrm{diag}\left([\mathcal{C}_{1,1,1,1,\boldsymbol{s}},\mathcal{C}_{2,2,2,2,\boldsymbol{s}},\cdots,\mathcal{C}_{P,P,P,P,\boldsymbol{s}}]\right)$. Recall that the p-th column vector of the Khatri-Rao product $\boldsymbol{A}\oslash\boldsymbol{A}$ is given by $[A_{1,p}\,\boldsymbol{a}_p{}^{\mathsf{T}},\cdots,A_{P,p}\,\boldsymbol{a}_p{}^{\mathsf{T}}]^{\mathsf{T}}$ where $A_{n,p}$ denotes the (n,p)-th component of $\boldsymbol{A}$.

B. Principle of the eJADE$^{(2)}$ approach

The first step of the eJADE$^{(2)}_{3,4}$ consists in computing a Singular Value Decomposition (SVD) of matrix $\boldsymbol{T}_{\boldsymbol{x}}^{(3,4)}$, say computing the following decomposition:

$$\boldsymbol{T}_{\boldsymbol{x}}^{(3,4)}=\boldsymbol{U}\,\boldsymbol{D}\,\boldsymbol{V}^{\mathsf{T}} \tag{4}$$

where $\boldsymbol{D}$ is a $(P\times P)$ positive semi-definite diagonal matrix and where $\boldsymbol{V}^{\mathsf{T}}\boldsymbol{V}=\boldsymbol{U}^{\mathsf{T}}\boldsymbol{U}=\mathbf{I}_P$ with $\mathbf{I}_P$ the $(P\times P)$ identity matrix. From (3), we can show that:

$$\boldsymbol{V}=(\boldsymbol{A}\oslash\boldsymbol{A})\,\boldsymbol{Q} \tag{5}$$

where $\boldsymbol{Q}$ is a $(P\times P)$ non-singular matrix. Let Q_{p_1,p_2} be the (p_1,p_2)-th entry of $\boldsymbol{Q}$. By writting $r_1=p_2+P(p_1-1)$, we derive from (5) that the (r_1,r_2)-th entry, V_{r_1,r_2}, of matrix $\boldsymbol{V}$ has the following expression:

$$V_{r_1,r_2}=\sum_{r_3=1}^{P}Q_{r_3,r_2}\,A_{p_1,r_3}\,A_{p_2,r_3} \tag{6}$$

Now, let's build the P matrices $\boldsymbol{V}^{(r_2)}$ of size $(P\times P)$, whose (p_1,p_2)-th entry, $V^{(r_2)}_{p_1,p_2}$, is given by $V^{(r_2)}_{p_1,p_2}=V_{p_2+P(p_1-1),r_2}$. Then, for every $1\leq r_2\leq P$, we have:

$$\boldsymbol{V}^{(r_2)}=\boldsymbol{A}\,\boldsymbol{Q}^{(r_2)}\boldsymbol{A}^{\mathsf{T}} \tag{7}$$

where $\boldsymbol{Q}^{(r_2)}=\mathrm{diag}\left(\boldsymbol{Q}(:,r_2)\right)$ is a $(P\times P)$ diagonal matrix whose diagonal components are the elements of the r_2-th column of $\boldsymbol{Q}$. So, a joint diagonalization of the P matrices $\boldsymbol{V}^{(r_2)}$ using for instance the JAD technique [4] (and not the JADE algorithm [3]) or the ELSALS$_{\mathrm{sym}}$ scheme [12] allows us to identify the orthogonal mixing matrix $\boldsymbol{A}$. Note that the eJADE$^{(2)}_3$ method can be identically described provided that the $(M\times P^2)$ matrix $\boldsymbol{T}_{\boldsymbol{x}}^{(3,4)}$ is replaced by the $(P\times P^2)$ matrix $\boldsymbol{T}_{\boldsymbol{x}}^{(3)}$ entrywise given by $T^{(3)}_{m_1,m_2,\boldsymbol{x}}=\mathcal{C}_{p_1,p_2,m_1,\boldsymbol{x}}$ with $m_2=p_2+P(p_1-1)$.

IV. Performance comparison of ICA methods on MRS and EEG signals

This section aims at comparing the performance of eleven ICA methods, namely CoM2 [5], INFOMAX [13], JADE$^{(1)}_4$ [3], JADE$^{(2)}_4$ [3], eJADE$^{(1)}_3$ [15], eJADE$^{(1)}_{3,4}$ [15], CubICA$_3$ [2], CubICA$_4$ [2], CubICA$_{3,4}$ [2], eJADE$^{(2)}_3$ and eJADE$^{(2)}_{3,4}$, on MRS and EEG synthetic signals.

A. Cumulant informative degree and performance criterion

First of all, we propose the following criterion to measure the q-th order Cumulant Informative Degree (CID) associated to a bidimensional random vector $\boldsymbol{s}$ with unit-variance components:

$$\mathit{CID}^{(q)}_{\boldsymbol{s}}=\frac{|\mathcal{C}_{1,\ldots,1,\boldsymbol{s}}|+|\mathcal{C}_{2,\ldots,2,\boldsymbol{s}}|}{\sum_{p_1}^{2}\cdots\sum_{p_q}^{2}\left|\mathcal{C}_{p_1,\ldots,p_q,\boldsymbol{s}}\right|(1-\delta[p_1,\ldots,p_q])} \tag{8}$$

where the generalized Kronecker symbol δ is given by $\delta[p_1,\ldots,p_q]=1$ if $p_1=\ldots=p_q$ and $\delta[p_1,\ldots,p_q]=0$ otherwise. The $\mathit{CID}^{(q)}_{\boldsymbol{s}}$ criterion simply measures the diagonal character of the q-th order cumulant tensor of $\boldsymbol{s}$, say the statistical independence at order q of both components of $\boldsymbol{s}$.

Secondly, we propose to measure the error between the mixing matrix $\boldsymbol{A}$ and its estimate $\widehat{\boldsymbol{A}}$ using the following performance criterion [6]:

$$D(\boldsymbol{A},\widehat{\boldsymbol{A}})=\min_{\mathbf{\Pi}}\Psi(\boldsymbol{A},\widehat{\boldsymbol{A}}\,\mathbf{\Pi}) \tag{9}$$

where $\mathbf{\Pi}$ belongs to the set of permutations and where:

$$\Psi(\boldsymbol{A},\widehat{\boldsymbol{A}})=\sum_{p=1}^{P}\|\boldsymbol{a}_p-(\widehat{\boldsymbol{a}}_p^{\mathsf{T}}\,\boldsymbol{a}_p/\|\widehat{\boldsymbol{a}}_p\|^2)\,\widehat{\boldsymbol{a}}_p\| \tag{10}$$

It is noteworthy that the D criterion is invariant to scale and permutation indeterminacies inherent in ICA.

B. Magnetic resonance spectroscopic data

In the MRS context, it is assumed that the metabolites do not interact so that the static linear mixing model is valid. In addition, several studies [18] showed that ICA is able to decompose the MRS data into components with features typical of different brain tissue or lesion types. Eight observations (two of them are represented in figure 1), considered as a noisy mixture of one source of interest, namely the N-Acetyl Aspartate (NAA) metabolite, and one artifact source such as the lipid metabolite, are generated. Each metabolite spectrum (one realization is depicted in figure 1) is built using a lorentzian function where the parameters (location and scale parameters) are fixed to derive realistic NAA and lipid-like metabolites. As far as the additive noise is considered, a

	-15dB	-10dB	-5dB	0dB	5dB
COM2	1.2077	1.0499	0.7803	0.4560	0.2103
INFOMAX	1.2114	1.0773	0.8148	0.4722	0.2141
eJADE$^{(1)}_{34}$	1.2079	1.0506	0.7818	0.4566	0.2105
JADE$^{(1)}_{4}$	1.2076	1.0499	0.7803	0.4560	0.2103
eJADE$^{(1)}_{3}$	1.2099	1.0671	0.8404	0.5060	0.2277
CubICA$_{34}$	1.2187	1.1679	1.1099	0.0891	0.0455
CubICA$_{4}$	1.2187	1.1680	1.1084	0.0898	0.0456
CubICA$_{3}$	1.1654	0.7142	0.1509	0.0622	0.0427
eJADE$^{(2)}_{34}$	1.1769	0.6981	0.1511	0.0640	0.0417
JADE$^{(2)}_{4}$	1.1773	0.7463	0.1567	0.0642	0.0417
eJADE$^{(2)}_{3}$	1.1481	0.6966	0.1468	0.0608	0.0413

TABLE I

CRITERION D AT THE OUTPUT OF THE 11 ICA METHODS AS A FUNCTION OF SNR IN THE CONTEXT OF MRS DATA

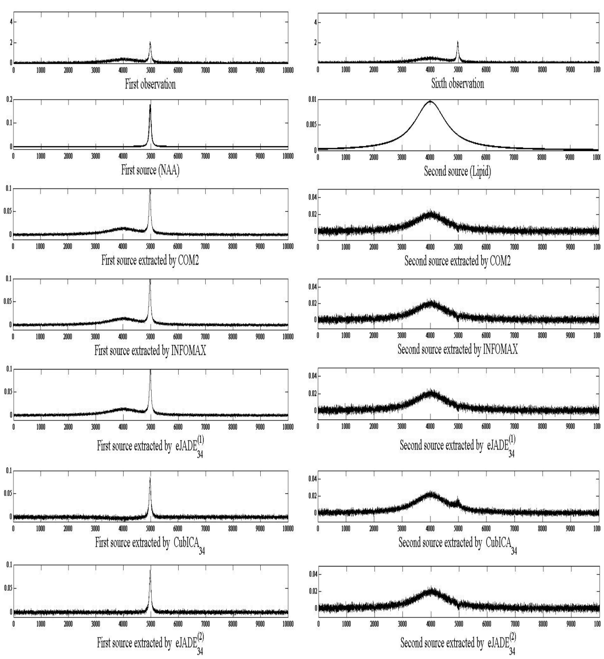

Fig. 1. Median over 30 realizations of the sources at the output of CoM2, INFOMAX, eJADE$^{(1)}_{34}$, CubICA$_{34}$ and eJADE$^{(2)}_{34}$ in the context of MRS data (SNR=0 dB)

Gaussian vector process is used to simulate the instrumental noise. Regarding the mixing matrix A, it is defined as the concatenation of two columns modelling the concentration of the NAA and the lipid. Finally, all reported results are obtained by calculating the median over 30 independent experiments.

Table I shows the D criterion at the output of the eleven ICA methods as a function of the Signal-to-Noise Ratio (SNR). The eJADE$^{(2)}_{3}$ method clearly gives the best results. Next, three methods, namely CubICA$_3$, eJADE$^{(2)}_{34}$ and JADE$^{(2)}_{4}$, show similar and good results. Eventually, the seven other methods seem to be less efficient, especially the eJADE$^{(1)}$ and JADE$^{(1)}$ techniques. This shows the interest of the eJADE$^{(2)}$ implementation, say in efficiently reducing the number of cumulant matrices before jointly diagonalizing them. This result is confirmed in figure 1, which displays both sources at the output of CoM2, INFOMAX, eJADE$^{(1)}_{3,4}$, CubICA$_{3,4}$ and eJADE$^{(2)}_{3,4}$. The first source estimated by eJADE$^{(1)}_{3,4}$ is clearly a mixture of the NAA and lipid metabolites whereas eJADE$^{(2)}_{3,4}$ succeeds in extracting both metabolites. The fact that eJADE$^{(2)}_{3}$ gives better results than JADE$^{(2)}_{4}$ is in total agreement with the CID values computed at orders 3 and 4, respectively, from the bidimensional vector $\boldsymbol{s}$ of the NAA and lipid metabolites. Indeed, we get $\mathit{CID}^{(3)}_{\boldsymbol{s}} = 6,7932$ and $\mathit{CID}^{(4)}_{\boldsymbol{s}} = 4,3927$, which shows that the TO cumulants are more informative than the FO ones and which justifies their use in the case of MRS data.

C. Electroencephalographic signals

In the particular context of epileptic patients, for whom EEG remains a key diagnosis tool, ICA is suitable for denoising purposes, when electrophysiological events such as interictal spikes or ictal discharges are masked by artifacts, particularly muscle activity [14]. Indeed, EEG can be considered as a static linear mixture of such activities, assumed mutually independent due to their different physiological origins [10]. However, there is still few studies attempting to validate ICA approaches using data for which the sources of EEG activity are known a priori. In this study we focus on the denoising of EEG data in the particular case of epileptic interictal spikes. The simulated EEG data (two observations are displayed in figure 2), are generated using a realistic head model [7], [8], that consists in three nested homogenous volumes realistically shaping the brain, the skull and the scalp, respectively. More precisely, two distributed sources, referred to as "patches" in the sequel and related to interictal spikes, are simulated. One patch is defined in the left superior temporal gyrus, and another one is given in the left supramarginalis gyrus. Each patch is composed of 100 dipole sources assigned with hyper-synchronous (and so very close) spike-like activities. These activities were kept independent between the two patches (their mean is displayed in figure 2). From this setup, and using 18 electrodes, the forward problem is then calculated giving a mixing matrix $A = [A_1, A_2]$, where A_1 and A_2 are two (18×100) matrices associated with patch 1 and 2, respectively. Uncorrelated background activities are attributed to the remaining part of the cortical activity. 30 trials of these simulated EEG are generated for the study. A different muscle activity issued from real EEG data is added to each of them.

The D criterion, computed at the output of the eleven ICA methods as a function of the SNR, is displayed in table II. All methods seem to give good results, except eJADE$^{(1)}_{3}$, eJADE$^{(2)}_{3}$ and CubICA$_3$ as announced by the CID values computed at orders 3 and 4, respectively, from the bidimensional vector $\boldsymbol{s}$ of the mean activities of both patches: $\mathit{CID}^{(3)}_{\boldsymbol{s}} = 5,2036$ and $\mathit{CID}^{(4)}_{\boldsymbol{s}} = 9,0764$. It appears that FO cumulants are practically twice more informative than TO cumulants. This result points out the robustness of eJADE$^{(2)}_{3,4}$ with respect to weakly informative TO cumulants. Figure 2

	-15dB	-10dB	-5dB	0dB	5dB
COM2	0.7835	0.4246	0.2125	0.1481	0.1270
INFOMAX	0.7823	0.3881	0.2312	0.1432	0.1261
$\text{eJADE}_{34}^{(1)}$	0.7557	0.4268	0.2132	0.1480	0.1270
$\text{JADE}_{4}^{(1)}$	0.7556	0.4252	0.2129	0.1480	0.1270
$\text{eJADE}_{3}^{(1)}$	1.5583	1.2683	0.8693	0.6943	0.5402
CubICA_{34}	0.8264	0.4265	0.2171	0.1515	0.1344
CubICA_{4}	0.8130	0.4231	0.2157	0.1506	0.1344
CubICA_{3}	1.6185	1.2134	0.8896	0.6401	0.4772
$\text{eJADE}_{34}^{(2)}$	0.7568	0.3901	0.2048	0.1471	0.1306
$\text{JADE}_{4}^{(2)}$	0.7532	0.3801	0.2011	0.1467	0.1305
$\text{eJADE}_{3}^{(2)}$	1.5964	1.2652	0.8749	0.6081	0.5132

TABLE II

CRITERION D AT THE OUTPUT OF THE 11 ICA METHODS AS A FUNCTION OF SNR IN THE CONTEXT OF EEG DATA

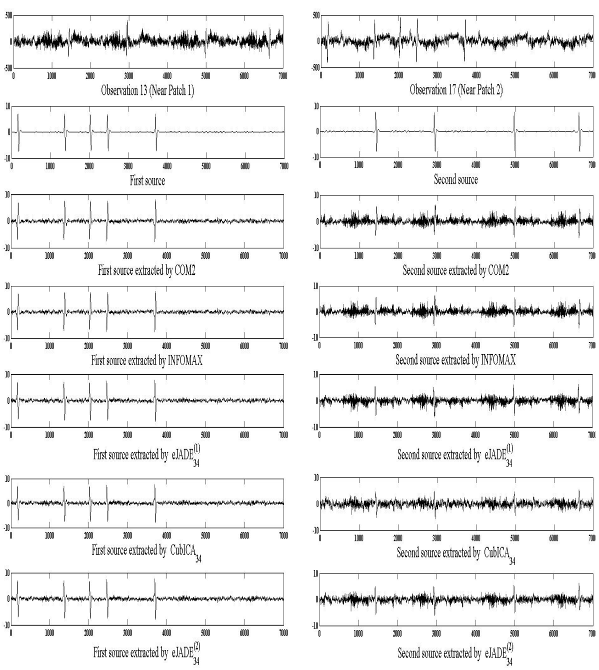

Fig. 2. Both sources at the output of COM2, INFOMAX, $\text{eJADE}_{34}^{(1)}$, CubICA_{34} and $\text{eJADE}_{34}^{(2)}$ in the context of EEG data (SNR$= -10$ dB)

confirms the good behavior of $\text{eJADE}_{3,4}^{(2)}$ with respect to other methods.

V. CONCLUSION

In order to perform ICA, an efficient way of jointly using SO, TO and FO statistics is proposed, leading to the $\text{eJADE}_{3,4}^{(2)}$ method. The latter can be interpreted as an improvement of the $\text{eJADE}_{3,4}^{(1)}$ technique. The SVD-based reduction of the set of TO and FO cumulant matrices to be jointly diagonalized is shown to considerably improve performance in the case of MRS signals. Interestingly, poorly informative TO cumulants as observed in EEG do not affect performance of $\text{eJADE}_{3,4}^{(2)}$, which encourages us to combine them with FO cumulants in all contexts. It is noteworthy that all tests were made using realistic synthetic signals in order to allow for a quantitative comparison of eleven ICA methods, most of them based on the use of HO cumulants.

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