JOINT BSS AS A NATURAL ANALYSIS FRAMEWORK FOR EEG-HYPERSCANNING

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ABSTRACT

Recent advances in Joint Blind Source Separation (JBSS) extend the BSS framework to the simultaneous source separation of multiple datasets. In this paper we provide a comparative study of four such JBSS algorithms on human dual-electroencephalographic (dual-EEG) data. Appropriateness of second order JBSS is demonstrated for concurrent estimation of correlated sources in a multi-subject synchronous steady-state visually evoked potentials experiment. This approach gives a new starting point for the exploration of brain activities in a hyperscanning framework.

Index Terms— Hyperscanning, joint BSS, SSVEP, dual-EEG, Brain Coupling.

1. INTRODUCTION

Blind Source Separation (BSS) finds major use in many application fields such as biomedical engineering, telecommunications, or audio, acoustics and speech processing [1]. This data-driven approach consists in estimating unobserved sources from a single set of multiple linear mixtures with minimal a priori knowledge. Now what if one seeks for a simultaneous separation of sources from multiple datasets? This question was addressed recently in the signal processing community with applications in speech processing [2] and medical data analysis [3,4,5].

The extension of BSS to multiple data sets –devised "Joint Blind Source Separation" (JBSS)– provides a natural framework for group inferences in medical imaging data collected from multiple subjects, or for data fusion from multiple modalities [6]. In this paper, we highlight its special interest in real-world scenarios where data are recorded from two or more subjects simultaneously, a recent neuro-imaging modality coined as "hyperscanning" [7]. Hyperscanning allows the study of both intra- and inter-subject cerebral processes through the joint analysis of data acquired from all individuals during social interaction. Most EEG-hyperscanning studies have performed analysis at the sensor level, although this may be inappropriate in many respects. From a physiological point of view, due to high individual variability of the cortical folding there is no reason to assume that similar neural activity in different subjects results in the same EEG pattern on the scalp. From a statistical point of view, making inferences from all pair-wise sensor synchronicity measures decreases statistical sensitivity and leads to ad hoc clustering procedures to reduce the data dimension (e.g. [8,9]). In this manuscript, we show that JBSS provides an appropriate framework for analysis of EEG-hyperscanning data *at the source level*. Using hyperscanning, neuroscientists assume that neural activities are (at least in part) dependent across subjects in a given experimental situation. Why not incorporate this additional prior knowledge on source distribution when addressing the BSS problem? This can be done by imposing cross-correlation or higher-order source dependence across datasets. Keeping the assumption of source independence within datasets, JBSS exploits such coupling resulting in performance beyond what is achievable with single-set BSS applied to each dataset individually [10].

In this paper, we evaluate the appropriateness of using JBSS algorithms for the analysis of hyperscanning data. To do so, we acquired EEG data during a two-subject steady-state visually evoked potentials (SSVEP) experiment. SSVEPs are natural responses of the visual cortex in which the neuronal activity becomes phase-locked to external visual stimulations ranging from 3.5 Hz to 90 Hz (for a review, see [11]). Here, subjects were stimulated simultaneously with trains of 10 seconds of flash stimulations at specified frequencies of 8 or 13 Hz. In this experimental set-up, it is of particular interest that SSVEPs were *synchronously elicited in both brains.* Hence visual cortices were implicitly coupled to each other by means of a common external trigger, i.e. their neural activities were assuredly phase-locked at specified frequencies.

Experimentally controlled brain-to-brain coupling during simultaneous visual stimulation gives a relevant framework for EEG data analysis using joint BSS. To some extent it provides us with a benchmark for the comparison of multiple second order (J)BSS algorithms on real-world data. Using prior knowledge of the frequencies of flash stimulations, we compare the performances of different algorithms based on 1) measures of mean squared coherence (MSC) between inter-subject pairs of source estimates, and 2) source frequency fitting to expected SSVEPs spectrum.

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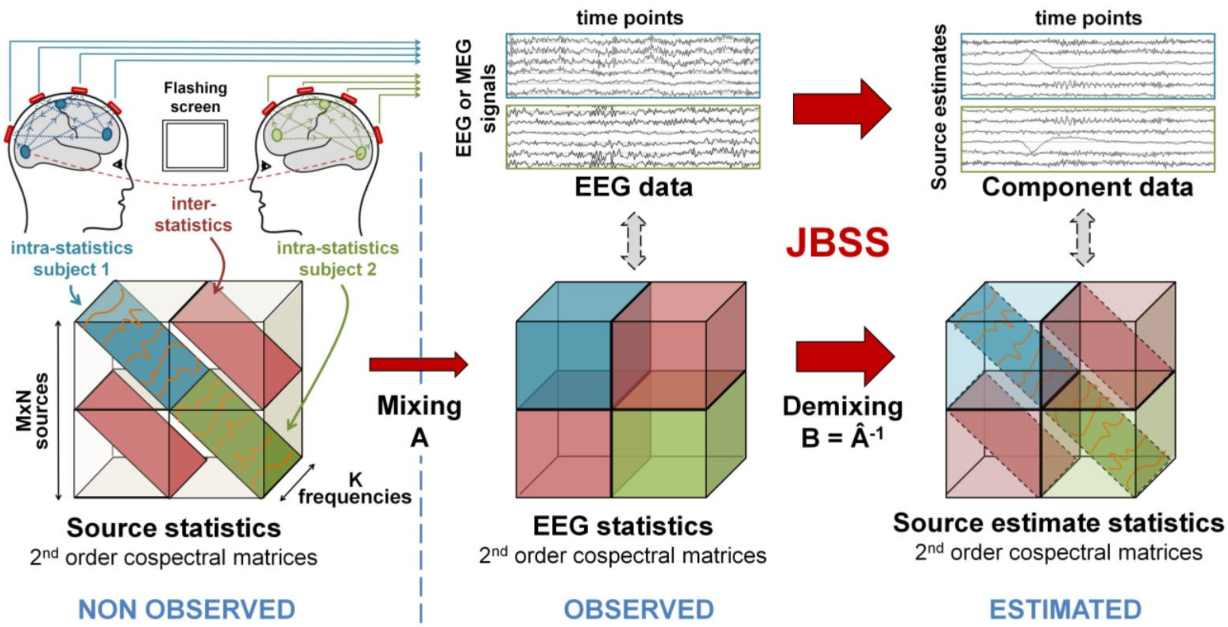

Figure 1. Illustration of JBSS applied to dual-EEG data. When using cospectral information, assumptions on 2nd order source dependence across datasets and 2nd order source independence within datasets enable to estimate the two demixing matrices.

Specifically, we hypothesize that JBSS algorithms should give better results than single-set BSS in the extraction of SSVEP components, benefiting from source cross-correlation between subjects.

2. METHOD

2.1. Joint BSS problem statement

In JBSS two main assumptions are made on source mixture model. First, we keep the typical BSS constraint implying independent sources when they belong to the same dataset. Second, JBSS incorporates additional prior knowledge on source distribution in assuming cross-correlation or higher-order source dependence *across* datasets. An additional assumption is made in imposing source *alignment*, i.e., the order of corresponding sources estimates must be the same for all datasets. This last constraint leads to a one-to-one correspondence of sources between datasets. Although permutation ambiguity is still present when separating sources, in the mixture model permutation is forced to be identical for every dataset. The three aforementioned hypotheses imply a multi-diagonal structure on matrices of source statistics; see Fig. 1 for an illustration. Second order JBSS algorithms deal with this separation problem in jointly *diagonalizing* multiple datasets of source statistics.

We now formulate the JBSS problem. There are M datasets, each formed from linear mixtures of P independent sources, each containing T samples. We assume the following generative model for the data:

$$\boldsymbol{x}_{\mathrm{m,k}}(t) = \boldsymbol{A}_{\mathrm{m}}\boldsymbol{s}_{\mathrm{m,k}}(t) \tag{1}$$

$$1 \leq \mathrm{m} \leq \mathrm{M},\ 1 \leq \mathrm{t} \leq \mathrm{T},\ 1 \leq \mathrm{k} \leq \mathrm{K},$$
$$\boldsymbol{x}_{\mathrm{m,k}}(t) \in \mathbb{R}^{N},\ \boldsymbol{A}_{\mathrm{m}} \in \mathbb{R}^{N\mathrm{x}P},\ \boldsymbol{s}_{\mathrm{m,k}}(t) \in \mathbb{R}^{P},$$

In the specific case of dual-EEG, $\boldsymbol{x}_{\mathrm{m,k}}(t)$ is a vector of N electrode signals sampled at time t and we have *M=2* datasets. Index k refers to different observations available for each signal, or different statistics computed from these signal, e.g., cospectral matrices at specified frequencies. $\boldsymbol{s}_{\mathrm{m,k}}(t)$ is a vector holding the t^{th} time sample of P≤N source components. $\boldsymbol{A}_{\mathrm{m}}$ is a time-invariant full column rank mixing matrix applied to the m^{th} set of source components. Notice that the mixing matrix is specific to each dataset, but is the same for each dataset along the K statistics layers. This model is an extension to multiple datasets of the typical joint diagonalization model found in the BSS literature. It reduces to the standard BSS model when only one dataset is available (*M=1*).

Here, as in BSS of single datasets, the sources and the mixing matrix can only be identified up to an arbitrary scaling ambiguity [1]. However with JBSS we impose an alignment of sources across datasets i.e., $\hat{\boldsymbol{s}}_m = \mathbf{P}\,\boldsymbol{\Lambda}_{\mathrm{m}}\boldsymbol{s}_m$, where P is an arbitrary permutation matrix that is common to all datasets and Λ_{m} is a full rank diagonal matrix.

To apply JBSS we estimate K[M(M+1)/2] matrices of statistics. From Eq. (1) these matrices are of the form:

$$\boldsymbol{C}_{\mathrm{ij,k}} = \boldsymbol{A}_{\mathrm{i}}^{T}\boldsymbol{\Lambda}_{\mathrm{ij,k}}\boldsymbol{A}_{\mathrm{j}} \tag{2}$$

$$1 \leq \mathrm{i,j} \leq \mathrm{M}\,,\ 1 \leq \mathrm{k} \leq \mathrm{K}$$

$\boldsymbol{\Lambda}_{\mathrm{ij}}$ matrices are the unknown source statistics and are supposed all diagonal. In order to estimate the M demixing matrices we seek the pseudo-inverse of the mixing matrices forming all $\boldsymbol{B}_{\mathrm{i}}\boldsymbol{C}_{\mathrm{ij,k}}\boldsymbol{B}_{\mathrm{j}}^{T}$ products yielding as much as possible a diagonal form. This implies that the output statistics within datasets (i.e., for i=j) are diagonalized as in the BSS framework, we denote these "intra-statistics". In addition, the output cross-statistics between datasets (i.e., for i≠j) are also diagonalized, we denote these "inter-statistics".

2.2. Presentation of the algorithms

In this comparative study we ignore higher-order statistics and focus on second-order statistics only, since they adequately capture induced EEG activity [12]. Therefore we chose algorithms that exclusively exploit sample-to-sample dependence (i.e. source coloration) to improve source separation. Here we tested one state-of-the-art single-set BSS algorithm (U-WEDGE) and three JBSS algorithms (JDIAG-SOS, OJoB, NOJoB). To the best of our knowledge, to date there are no other JBSS algorithms exploiting sample-to-sample dependence.

U-WEDGE [13] is a non-orthogonal least-square approximate joint diagonalization (AJD) algorithm with fast implementation based on Gauss iterations. JDIAG-SOS [14] is an orthogonal algorithm that iteratively solves orthogonal Procrustes problems for the AJD of 2nd order statistics, and then performs a gradient search when M is small. OJoB and NOJoB [15] are, respectively, orthogonal and non-orthogonal JBSS algorithms based on power iterations. All the aforementioned JBSS algorithms seek to minimize off-norm cost functions in the least-square sense as described here below (4). However, they differ in the part of the criterion that is minimized, i.e., the type of source statistics used to achieve separation. Indeed, in JBSS the cost function can be divided into two terms [14,15]:

$$\psi(\boldsymbol{B}_m) = \sum_{m=1}^{M} \psi_{intra}(\boldsymbol{B}_m) + \psi_{inter}(\boldsymbol{B}_m)\,, \tag{4}$$

where

$$\psi_{intra}(\boldsymbol{B}_m) = \sum_{k=1}^{K} \left\| \mathrm{off}\left[\boldsymbol{B}_{\mathrm{m}}\, \boldsymbol{C}_{\mathrm{mm,k}}\, \boldsymbol{B}_{\mathrm{m}}^{T}\right]\right\|_F^2 \tag{5}$$

and

$$\psi_{inter}(\boldsymbol{B}_m) = \sum_{k=1}^{K} \sum_{i\neq m}^{M} \left\| \mathrm{off}\left[\boldsymbol{B}_{\mathrm{m}}\, \boldsymbol{C}_{\mathrm{mi,k}}\, \boldsymbol{B}_{\mathrm{i}}^{T}\right]\right\|_F^2 . \tag{6}$$

In the above formulas off(X) sets the diagonal elements of X to zeros and $\| \|_F$ denotes the Frobenius norm. Note that ψ_{intra}(5) is actually a sum of classical joint diagonalization costs for BSS, where one only deals with intra-statistics to achieve separation. When solely ψ_{intra} is considered, extracting sources from multiple datasets simply amounts to performing BSS on each dataset separately. This cost is the one used in U-WEDGE algorithm. By contrast, JDIAG-SOS relies on inter-statistics in the minimization of cost ψ_{inter} only, and then minimizes the whole cost function when M is small [14]. Finally, OJoB and NOJoB algorithms seek simultaneous minimization of ψ_{intra} and ψ_{inter} in considering the whole cost function (4). Overall strategies for JBSS consist in performing an alternating search for each matrix $\boldsymbol{B}_{\mathrm{m}}$ and iterate until convergence.

2.3. Processing workflow

EEG data were acquired at sampling rate 128Hz using separate reference and ground with 16 electrodes for each subject. Amplifiers were connected to the same clock, which guaranteed synchronous recordings. Cospectra were estimated for each SSVEP periods by means of Welch's method with 75% overlapping Hamming windows of 512 points, i.e. frequency resolution of 0.25Hz. Cospectral estimates were then averaged over 30 flashing periods with length 10 seconds at 8 or 13 Hz. Finally (J)BSS was applied on these cospectral matrices selected in range 5-28Hz only.

We next quantify the frequency-specific synchronization between inter-subjects pairs of source estimates using mean squared coherence [16]. MSC measures the linear correlation between two time series at each frequency. At a given frequency, if the phase of one signal is fixed relative to the other then the signals generally have a high coherence. We processed coherence in a pair-wise fashion for all P^2 source combinations between subjects. This last procedure accounts for possible source permutations in the case where algorithms do not manage to align the estimated sources across subjects. Pairs of source estimates were then sorted based on their average MSC value at flashing frequencies and their first harmonics ($\mathrm{Coh}_{\mathrm{FLASH}}$). This spectral fitting measure enables to identify coupled SSVEP sources across subjects and to quantify this coupling in terms of squared coherence. Finally we derived a simple discrimination score for SSVEP sources estimation as the ratio of $\mathrm{Coh}_{\mathrm{FLASH}}$(1st pair) to $\mathrm{Coh}_{\mathrm{FLASH}}$(2nd pair). High discrimination score means that SSVEP sources were selectively extracted within the first source pair, while other pairs do not report about neural activity phase-locked to flashing stimuli.

3. RESULTS

In this section we detail the behavior of tested algorithms for the extraction of SSVEP source estimates in both subjects. Fig. 2 (left) shows the MSC profiles of inter-subjects pairs of sources that best explain the flashing frequencies. All algorithms display a high coherence in these frequencies, suggesting that they were able to capture the SSVEP source of activity. They retrieved high MSC values in both flashing frequencies and their harmonics, a result consistent with literature on SSVEPs [11]. If we confine the analysis to the best matching pairs of source estimates only, the important overlapping of coherence profiles seems to indicate that tested algorithms exhibit close performances. In order to have a complete view of the separation and its quality, one should take a closer look to the other pairs of source estimates as well. As depicted in fig. 2 (right), average MSC in flashing frequencies of the 10 first pairs does not exhibit the same behavior between algorithms. While for JBSS algorithms MSC decrease quickly after the first pair of source estimates, it is not the case for U-WEDGE BSS algorithm for which pairs 2 to 10 show the highest MSC among the algorithms used. This means that SSVEP source

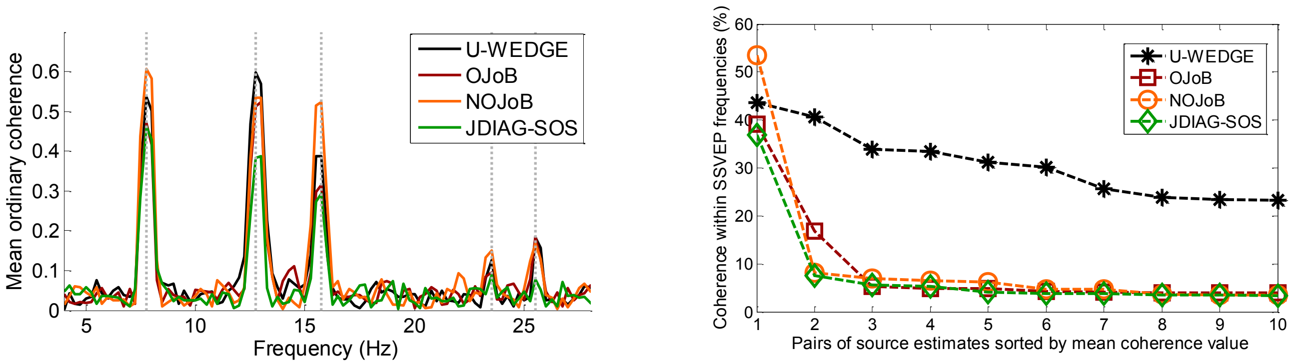

Figure 2. Left: coherence profiles of pairs of source estimates. Best pairs were chosen in terms of highest spectral fitting to SSVEP flashing frequencies. Grey dotted lines correspond to flashing frequencies at 8 and 13 Hz and their corresponding harmonics. Right: MSC concentration in SSVEP flashing frequencies (Coh_{FLASH} / Coh_{TOTAL}) for the 10 first pairs of sources estimates.

was split into numerous components during the extraction. We can summarize this behavior sketching the discrimination score and average MSC for the best pair of source estimates (Fig. 3). Here NOJoB algorithm provides superior performance in average, with the largest coherence for first pair of source estimates and best discrimination of SSVEP flashing frequencies. Interestingly, all JBSS algorithms have their most coherent source pair aligned, i.e. indexes of these source estimates are the same for each subject. On the opposite, U-WEDGE displays a source permutation for its most coherent pair across subjects. Finally, we also tested AJSVD algorithm proposed in [3], which gave very similar results to JDIAG-SOS, probably because both minimize similar criterion with the same orthogonality constraint.

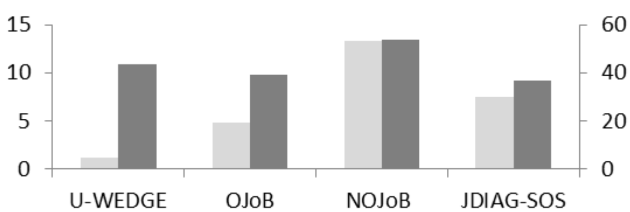

Figure 3. Light gray, left axis: discrimination scores for source extraction. Dark gray, right axis: MSC concentration in SSVEP flashing frequencies for the first pair of source estimates

4. DISCUSSION

In this comparative study we studied the effectiveness of the JBSS approach over a single-set BSS in the context of EEG-hyperscanning SSVEP source extraction. The central issue in choosing a specific analysis approach is which prior knowledge about sources is used to achieve "blind" separation. The algorithms presented here differ with respect to this point. Since it is based on intra-statistics only, state-of-the-art U-WEDGE BSS algorithm cannot take advantage of source cross-correlation between datasets. In contrast, all JBSS algorithm do consider source inter-statistics in their cost function. In other words, with the JBSS approach one can benefit from additional information on sources. Of course, such supplementary prior knowledge is appropriate only if it fits well the behavior of unobserved sources. With SSVEP source extraction in a dual-EEG framework, it follows that JBSS approach naturally gives better results than single set BSS as we know that brain coupling exists between the subjects at SSVEP flashing frequencies.

A major advantage of JBSS over single-set BSS also lies in the implicit alignment of coupled sources across datasets. Solving the permutation ambiguity, JBSS eases the joint analysis of hyperscanning data and enables to avoid multiple comparisons and clustering procedures when applying inter-subject connectivity measures.

Another important issue is the orthogonality constraint on the demixing matrices. Whilst this constraint allows us to develop simple and computationally more efficient algorithms, it also limits the solution space examined. Since dropping the orthogonality constraints results in more degrees of freedom, a better fit to the model is to be expected. When the model is an adequate description for the data, this results in better performance.

Finally, we can ask whether it is appropriate to incorporate proper weights for the intra- and inter-statistics. Depending on the situation, useful information for source separation may be contained predominantly in the intra- or the inter-statistics. Whether a normalization step is necessary to optimally balance the inter- and the intra-statistics, will be a topic of our future studies.

5. CONCLUSION

In this comparative study, appropriateness of JBSS was demonstrated for joint estimation of coupled sources of SSVEPs from multiple subjects. The performance of different algorithms was discussed in terms of choice of criterion and orthogonality constraint on demixing matrices. Results support the idea of a general efficiency of joint BSS for problems involving incoherent sources within datasets and coherent sources between datasets. This approach gives new insights into JBSS relevance for the extraction of brain sources in a hyperscanning framework.

6. REFERENCES

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