34th Annual International Conference of the IEEE EMBS
San Diego, California USA, 28 August - 1 September, 2012

ErpICASSO: a Tool for Reliability Estimates of Independent Components in EEG Event-Related Analysis

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Abstract— **Independent component analysis and blind source separation methods are steadily gaining popularity for separating individual brain and non-brain source signals mixed by volume conduction in electroencephalographic data. Despite the advancements on these techniques, determining the number of embedded sources and their reliability are still open issues. In particular to date no method takes into account trial-to-trial variability in order to provide a reliability measure of independent components extracted in Event Related Potentials (ERPs) studies. In this work we present *ErpICASSO*, a new method which modifies a data-driven approach named ICASSO for the analysis of trials (epochs). In addition to ICASSO the method enables the user to estimate the number of embedded sources, and provides a quality index of each extracted ERP component by combining trial-to-trial bootstrapping and CCA projection. We applied *ErpICASSO* on ERPs recorded from 14 subjects presented with unpleasant and neutral pictures. We separated potentials putatively related to different systems and identified the four primary ERP independent sources. Standing on the confidence interval estimated by *ErpICASSO*, we were able to compare the components between neutral and unpleasant conditions. *ErpICASSO* yielded encouraging results, thus providing the scientific community with a useful tool for ICA signal processing whenever dealing with trials recorded in different conditions.**

I. INTRODUCTION

Single-trial ERP data have been historically dealt with by averaging so as to increase the signal-to-noise ratio and highlight changes in subject state possibly linked to fluctuations in expectation, attention or other factors [14]. Recently however, as averaging may hide response variations in amplitude, time course and scalp distribution across trials, research is orienting towards methods, each based on different hypotheses, able to highlight these factors like microstate analysis [15], parallel factor analysis [21] and so on. In particular, Independent component analysis (ICA) has been widely adopted to analyze single-trial multichannel EEG data from ERP experiments [5], [13], [14], [6]. ICA blindly separates the input data into temporally-independent and spatially-fixed components arising from distinct brain or extra-brain sources [14], [19], [20], [7], [18]. A great number of different ICA algorithms share the "independence maximization" goal [17] (to date the most used ones are probably Second-Order Blind Identification [23], extended Infomax ICA [17], [4] and FastICA [12]) and generally yield similar results on simulated data. Nevertheless, as real EEG source signals are not perfectly independent and limited in recording time, different ICA algorithms often return different results. As such, increasing effort is being devoted to comparing the effectiveness of most BSS and ICA algorithms [8] and the reliability of independent component estimates [11], [22]. Despite great improvements of BSS and ICA algorithms in recent years, no method takes into account the trial-to-trial variability, the dataset dimension and simultaneously provides a reliability measure of independent ERP components. Also, a key issue regarding all blind ERP decompositions is still that of determining the number of embedded sources.

In this work we present for the first time *ErpICASSO* [3], a substantial improvement of the readily available toolbox, ICASSO [11]. ErpICASSO approaches the IC-ERP decomposition by combining trial-to-trial bootstrapping and CCA projection [9]. It estimates the number of embedded sources and provides a reliability measure of each extracted ERP component. ErpICASSO addresses some of the issues of ICASSO (see discussion): basically it improves its clustering step by applying CCA projection only on independent components which are correctly parsed into different clusters, it selects the number of independent components by averaging the clusters quality indexes and performs trial-to-trial bootstrapping thus enabling its use on trials datasets. For demonstration purposes, the proposed algorithm has been applied to ERPs evoked on 14 subjects by unpleasant and neutral pictures.

II. MATERIALS AND METHODS

A. *Decomposition of ERPs with* ErpICASSO

The core of ErpICASSO is a data-driven approach named ICASSO [11], [22], specifically modified by us for the treatment of ERP trials, to disentangle components of ERPs deriving from the activity of independent brain sources and to estimate their reliability. Basically ErpICASSO is a clustering stage applied to several runs of an ICA algorithm on a trial-to-trial bootstrapped dataset. ErpICASSO consists of the following steps:

1.**Selection of the ICA algorithm** We considered the standard linear, noise-free ICA model $X = AS$ of signal matrix X derived from independent sources S linearly mixed by the matrix A. For the estimation of A and S, we used FastICA with symmetrical approach, turned-on stabilization, $\tanh$ as

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contrast function and skewness as fine-tune function. The whitening step within FastICA reduced the data dimension to the number of embedded sources n. We determined n as described at the end of this section.

2.**Multiple ICA runnings** We estimated M replicates of ICs using the FastICA algorithm. Each time the FastICA initial conditions were randomized, the trials from all-subjects recordings were bootstrapped and the resulting set concatenated so as to arrange them in the signal matrix X. X had m rows and $(p+q)\tau$ columns where m was the number of EEG channels, p and q were the number of neutral and unpleasant trials, respectively and τ the number of time points of each trial. FastICA gave an estimate of S (n rows and $(p+q)\tau$ columns) whose rows represented the n independent components and an estimate of the unmixing matrix W (m rows and n columns), that is the pseudoinverse of A: the columns of A represent the weight distribution across the scalp of the correspondent IC.

3. **IC replicates clustering** The replicates derived from the M runs were clustered according to their mutual similarities σ, defined as the absolute value of the correlation coefficient. We identified n disjoint clusters by means of an agglomerative hierarchical clustering (dendrogram) with the group average-linkage criterion as agglomeration strategy. The number of clusters was set so as to equal the data dimension after the reduction.

4. **Removal of ambiguous IC replicates** The FastICA runs that yielded two or more IC replicates grouped by the dendrogram in the same cluster were excluded from further analysis. This step significantly increased the reliability of the method since unreliable FastICA runs and outliers were removed from the start.

5. **Best IC replicates with reliability** For each cluster the best IC estimate was identified as the centroid of the replicates belonging to the cluster. The centroid is the IC within the cluster having the maximum sum of similarities to the other ICs in the cluster. For the reliability of the cluster, we used the quality index I_q defined as follows:

$$I_q(C_k) = \frac{1}{\#^2_{C_k}} \sum_{i,j \in C_k} \sigma_{ij} - \frac{1}{\#_{C_k} \#_{C_{-k}}} \sum_{i \in C_k} \sum_{j \in C_{-k}} \sigma_{ij}$$

where k identifies the cluster, $\#_{C_k}$ the number of IC replicates included in the cluster C_k whereas $\#_{C_{-k}}$ the number of IC replicates not included in the cluster C_k, and $\sigma_{ij} = |r_{ij}|$ is the similarity between the IC replicates i and j, that is the absolute value of the Pearson correlation coefficient r_{ij}. Concerning the visualization of clustering results, in addition to the dendrogram, ErpICASSO produces a similarity map where each component estimate is plotted as a point, and the distances $d_{ij} = \sqrt{1-\sigma_{ij}}$ between points are inversely related to the similarities between components. Moreover, ErpICASSO uses the Curvilinear Component Analysis (CCA) as a multidimensional scaling method in order to project the points in a two-dimensions space so as to obtain the similarity map that we also used in the Results section. I_q measures of the variability of the ICA decomposition and consequently it is related to the confidence intervals of the averaged trials in the independent component space.

6. **Activity templates and Best Activity Templates** For each FastICA run the activity templates (ATs) were derived by separating the component time series into epochs according to the concatenated trials and by splitting the epochs into those related to unpleasant stimuli (AT_U) and those related to neutral ones (AT_N). The same was done for the best activity templates (BATs) derived from the best IC replicates as defined in the step 5.

7. **Number n of embedded sources**

To determine the number n of embedded sources, within ErpICASSO the whole procedure (items 1-4) is repeated varying n, from 1 to 10. Each time the I_q^{avg} is the mean index of quality over the clusters: $I_q^{avg} = \frac{1}{n}\sum_{k=1}^{n} I_q(C_k)$. The fraction $\frac{N}{M}$ of "broken" runs that do not yield properly separated components (see step 4) and the explained variance V are also computed. The final number n of embedded sources corresponds to that with the maximum I_q^{avg}, $\frac{N}{M} < 0.3$, $V > 80\%$.

B. Experimental protocol and EEG processing

Participants to the experiment were fourteen healthy, young men. They gave their written informed consent and the study has been approved by the Local Ethics Committee. Each participant was shown a pseudo-random mixing of 60 emotionally neutral (objects or landscapes) and 30 unpleasant (animal threats or human mutilations) images from the International Affective Picture System (IAPS [16]). Presentation of two consecutive unpleasant images was software-denied. Each image was presented in the central field of view for $1s$ and separated from the next one by a blank time interval ranging from two to three seconds. While performing the task each participant was placed in a quiet and dark room on a comfortable armchair. During the presentations scalp EEG signals were acquired with a sampling rate of 500Hz by electrodes having contact impedance below $5K\Omega$ and referenced to the FCz potential. Channels were offline re-referenced to the average potential of the two earlobes (A1 and A2) in order to obtain nearly monopolar recordings. Movement artifacts and temporary declines of signal quality were detected by finding sudden signal power variations [1], [3], [2]. Signals were filtered both with a comb notch filter (10^{th} order, 50Hz-centered, 3.5Hz-wide) and with a bandpass one (0.1Hz-20Hz). Each trial corresponded to the portion of signals from 100ms before to 1000ms after the onset of the image stimuli, in this way each ERP trial was composed by 550 time points sampled on 29 channels. Trials containing ocular artifacted were detected [3], [1] and removed. We applied ErpICASSO on the concatenated unpleasant and neutral trials for all subjects.

III. RESULTS

The ICA-based ERP analysis stands on the fact that ERPs mark stimulus-related serial brain activations whose activities may temporally overlap. This property enabled us to model

Embedded sources	2	3	4	5	6	7	8	9
Explained variance (%)	69	79	82	84	87	88	90	91
I_q^{avg}	0.79	0.82	0.84	0.77	0.69	0.65	0.66	0.63
$\frac{N}{M}$	0.01	0.02	0.03	0.4	0.45	0.5	0.6	0.7

TABLE I

QUALITY INDEXES I_q^{avg}, EXPLAINED VARIANCE OF THE CLUSTERS FRACTION OF "BROKEN" RUNS $\frac{N}{M}$ VARYING THE NUMBER n OF EXTRACTED EMBEDDED SOURCES

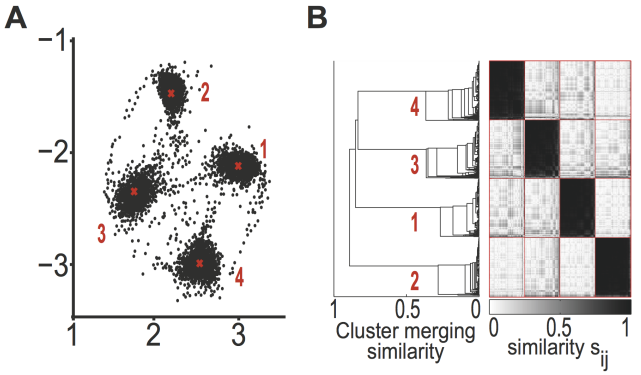

Fig. 1. **Similarity of the component estimates.** Panel A shows the similarity map, that is a scatterplot of the similarities between IC estimates on bootstrapped trial-to-trial projected in two dimensions by means of the Curvilinear Component Analysis (CCA [11]) used as a multidimensional scaling method. Each cluster centroid identifies the component from which the Independent components are derived. The tighter is the cluster, the greater the reliability of the related component. In the figure, the red numbers label the components and the red crosses identify the cluster centroids. Panel B shows both the dendrogram and the matrix of similarities of the component replicates. Clusters in the dendrogram are matched to the blocks within the matrix and labeled according to the similarity map.

ERPs as the sum of temporally-independent components arising from distinct, spatially-fixed, brain sources. ErpICASSO bases the component extraction on a ICA approach that estimates a demixing matrix W to transform trials data into independent components. The present analysis stands on the assumptions that all subjects have the same brain responses, and that arousal and valence of images modulate the time course of components but do not affect the location of the sources. Under these assumptions, the analysis is at a group-level: trials from all the subjects related to both neutral and unpleasant images were used to perform a unique, *group level* extraction of common brain sources. ErpICASSO not only yielded component estimates but also provided a reliability measure of each component by means of a quality index Q [11]. The quality index Q is based on the fact that robust components do not change while varying the specific dataset of trials. Accordingly, using statistical techniques belonging to bootstrapping approaches [10], ErpICASSO generates a replicate of each component from different samples of trials. In the case of robust components, the similarity between replicates is expected to be high for the replicates of the same component and low between replicates of different ones. We determined the number of embedded sources by using the criteria proposed in the methods section. Table 1

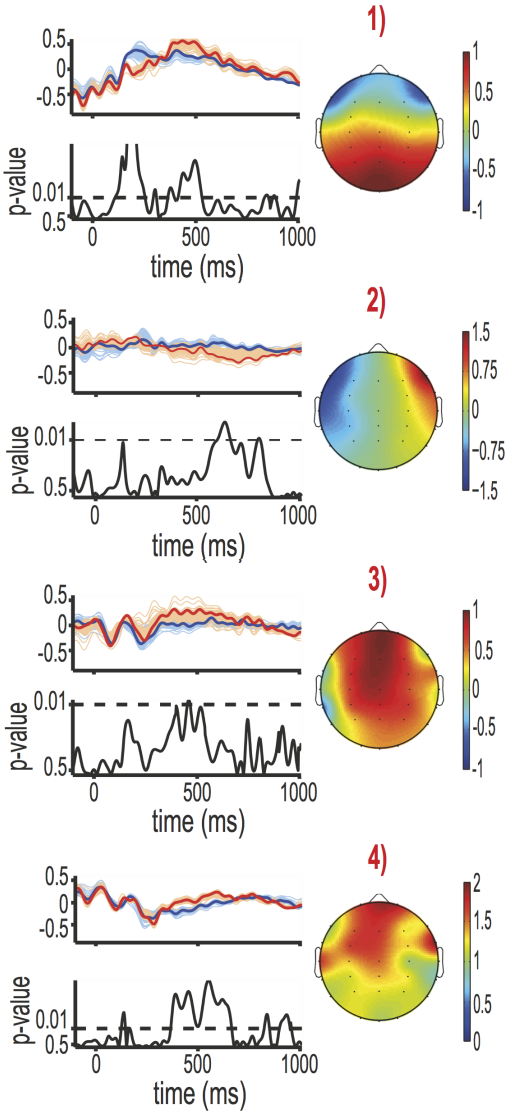

Fig. 2. **Best Activity Templates (BATs) with statistics and activation map.** The figure shows the sheafs of the activity templates (ATs), which are originated from the individual FastICA replicates that belong to each cluster. The sheafs were derived from the bootstrapping procedure within ErpICASSO and enable the estimation of IC confidence intervals. The red sheaf refers to the unpleasant responses, and the blue one to the neutral ones. Among ATs, the two BATs have been highlighted with thick lines. On the right of each plot, the figure also shows the correspondent activation map. Unpleasant and neutral BATs of each component share by construction the same activation map. The p-value time course below each plot indicates the intervals of significant differences between unpleasant and neutral BATs. P-values derived from comparing the two sheafs during each time of sampling (paired t test). The quality index of components 1, 2, 3, and 4 was 0.83, 0.82, 0.78 and 0.85, respectively.

shows the mean quality indexes, the explained variance and the fraction of components not correctly parsed into different clusters as a function of the selected n sources. We found a quality maximum for $n = 4$ (82% of the ERPs variance explained) which suggested to use 4 sources to model ERPs. For these four components, we obtained graphs of similarities between component replicates with well-defined clusters.

In figure 1 each IC replicate is plotted as a point on a two dimensions space: the IC location on this space is derived by a procedure that approximates the original dissimilarities between replicates by Euclidean distances in two dimensions. The centroid of each cluster is indicated by a red cross and corresponds to the best IC replicate. Figure 2 shows the topographic distribution of each activity component, with the BATs (thick lines), putatively different between unpleasants and neutrals. Indeed, as indicated by the sheaves of thin lines of the ATs and by the time-course of p-values obtained by testing the significance of differences, each BAT highlighted significant differences between unpleasants and neutrals at particular latencies.

DISCUSSION

In this work we present for the first time ErpICASSO [3], which modifies a data-driven approach named ICASSO [11], [22], for the treatment of ERP trials. ICASSO combines a bootstrapping approach and CCA projection [9] to provide a reliability estimate of the ICA extraction. ErpICASSO on the other hand takes into account the fact that the statistical unit is the trial instead of the time point, thus it is based on a trial-to-trial bootstrapping procedure. ErpICASSO provides the user with an estimation of the number of embedded sources by computing a quality index of each estimate and by examining the explained variance. Also it improves the ICASSO clustering step by applying CCA projection only on independent components which are correctly parsed into different clusters. This enabled to discard outliers and to better estimate each cluster centroid. Such confidence measures enable the user to determine not only the quality of data available but also whether the number of ERP trials available is sufficient for the analysis (which incidentally is another open issue in ICA approaches). To date none of the ICA and BSS methods available specifically address all these issues.

ErpICASSO has been applied on ERPs recorded from 14 subjects presented with unpleasant and neutral pictures. In this work the use of ErpICASSO allowed the separation of potentials putatively related to different systems and/or responsive to different conditions. Moreover it enabled us to identify the primary sources of the ERPs and allowed a data dimensionality reduction from 29 EEG scalp channels to 4 independent components that were able to explain most of the data variance. As a plus, the activity templates were extracted by ErpICASSO with confidence intervals, which enabled a comparison between conditions. Next steps in the development of the method will include validation on simulated data and a thorough study of its stability and performance varying the number of trials available for the analysis. We hope that ErpICASSO will provide the scientific community with more control over ICA decompositions and will constitute a useful tool not only in ERP analysis but also whenever dealing with trials recorded in different conditions.

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