INCORPORATING HIGHER DIMENSIONALITY IN JOINT DECOMPOSITION OF EEG AND FMRI

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ABSTRACT

EEG-fMRI research to study brain function became popular because of the complementarity of the modalities. Through the use of data-driven approaches such as jointICA, sources extracted from EEG can be linked to regions in fMRI. JointICA in its standard formulation however does not allow for the inclusion of multiple EEG electrodes, so it is a rather arbitrary choice which electrode is used in the analysis. In this study, we explore several ways to include the higher dimensionality of the EEG during a joint decomposition of EEG and fMRI. Our results show that incorporation of multiple channels in the jointICA can reveal new relations between fMRI activation maps and ERP features.

Index Terms— Multimodal, EEG-fMRI, joint decomposition, jointICA, coupled matrix-tensor decomposition

1. INTRODUCTION

Several technologies exist that can help to shed light on brain functioning. As data from one modality gives only a limited view on the phenomenon under investigation, there is a rising interest in methods that are able to combine data from different brain imaging modalities. In particular, two highly complementary modalities to study the brain are EEG and fMRI. There is a wide range of integration methods, but the family of data-driven decomposition techniques is of particular interest as they are able to extract sources from EEG and fMRI that are uniquely linked.

JointICA estimates independent components for both modalities simultaneously by assuming that different Event-Related Potential (ERP) peaks and spatial fMRI activation maps of the same stimulus co-vary, which could be physiologically explained by either that they are generated in the same brain region (see [3]), or that the fMRI BOLD-signal has a participatory role on the ERP-activity. As a result, jointICA provides linked sources in a data-driven fashion. JointICA was for the first time applied to fuse EEG-fMRI data in [2]. Later, the physiological validity of this technique was thoroughly tested in [6]. However, in its current implementation, it takes only one-dimensional data per subject as input, where EEG data is intrinsically higher dimensional. Traditionally, this one-dimensionality is achieved by selecting one electrode per subject "based on prior knowledge". As this can be often a rather arbitrary choice, we explore in this paper several possibilities of incorporating multiple dimensions in such a joint simultaneous decomposition of EEG and fMRI.

2. MATERIALS

2.1. Data acquisition

All experiments were performed on non-simultaneously acquired EEG-fMRI data recorded during a visual detection task. In order to be able to compare results in an objective way, we reuse the data from a jointICA study described in [6]. 18 subjects were subjected to a series of visual stimuli in the different quadrants of the visual field, and asked to press a button upon detection. First, fMRI was acquired during the tasks. Second, the experiment was repeated for EEG recording in a magnetic-field free environment. The data adopted only consisted to that corresponding to the visual stimuli in the down-left visual field quadrant. For details on data acquisition, we refer to [2,8].

2.2. Preprocessing

Preprocessing of the EEG was done in the MATLAB® environment. To make sure both modalities have equal impact on the decomposition, the EEG data were upsampled using cubic spline interpolation. Preprocessing of the fMRI was done using the SPM software. The fMRI data were slice—time corrected, realigned, coregistered with anatomical images, normalized to the MNI template and smoothed with 8-mm Gaussian Kernel. Percent Signal Change (PSC)

maps were derived from contrasting the BOLD signal invoked by a particular stimulus with the background.

3. METHODS

In this study, we aim to incorporate multiple channel dimensions in a joint decomposition of EEG and fMRI. We start from the original jointICA method, and modify its original formulation in order to incorporate information of multiple EEG channels.

The original jointICA model can be written as

$$[\boldsymbol{X}^{fMRI}\boldsymbol{X}^{EEG}] = \boldsymbol{A} \cdot [\boldsymbol{s}^{fMRI}\boldsymbol{s}^{EEG}] \quad (1)$$

Here, $\boldsymbol{X}$ corresponds to the observed signals, $\boldsymbol{s}$ denotes the sources, and $\boldsymbol{A}$ is the mixing matrix to be calculated. In this case, when one EEG channel is used as input, $\boldsymbol{X}^{EEG}$ is a $m \times n$ matrix, in which every row corresponds to the averaged ERP for one subject. The number of subjects thus equals m and the number of time samples equals n. $\boldsymbol{X}^{fMRI}$ is an $m \times p$ matrix, where every row corresponds to a vector containing all the voxels of a PSC fMRI map, p being the number of voxels.

The method works based on the assumption that the electrical effects of brain activation (ERP activity) and the hemodynamic response to this brain activation (BOLD response) are generated by the same neuronal activity. This means that stronger ERP peaks lead to stronger BOLD response. If this hypothesis is valid, the mixing matrix can be assumed to be common for EEG and fMRI, and this mixing matrix will reflect the relative strengths of the different peaks across subjects. Applying ICA to a matrix of concatenated PSC fMRI maps and averaged ERP signals will result in the extraction of components that link ERP peaks to activated regions in fMRI.
To compute ICA the Infomax algorithm by Bell and Sejnowski (1995), contained in the Fusion ICA Toolbox (FIT, Calhoun et al) was used. Since the number of extracted components needs to be determined in advance, first the robustness analysis tool ICASSO was used to determine the optimal numbers of components giving rise to stable solutions. The results of jointICA are presented based on 2 different EEG channels, namely PO8, and Oz, for which the results were previously shown in [6]. To be able to objectively compare the obtained fMRI maps, the fMRI sources are also normalized by subtracting the mean and dividing by the standard deviation.

One way to incorporate multiple channels and thus spatio-temporal ERP information is to concatenate multiple channels into the jointICA. This can be written as follows:

$$[\boldsymbol{X}^{fMRI}\boldsymbol{X}^{EEG_1}\boldsymbol{X}^{EEG_2} \dots \boldsymbol{X}^{EEG_n}] = \boldsymbol{A} \cdot [\boldsymbol{s}^{fMRI}\boldsymbol{s}^{EEG_1}\boldsymbol{s}^{EEG_2} \dots \boldsymbol{s}^{EEG_n}] \quad (2)$$

In this application of jointICA, the assumptions for which this model is valid remain the same. It implies that distinct ERP activity and fMRI maps are linked by their participatory role in certain brain activations. The results provide extracted sources that contain fMRI maps and –in this situation- an ERP peak as reflected on different electrodes. Since the results can be compared to the single-channel cases for electrodes PO8 and Oz, (2) is solved for electrode combinations including at least one of the original channels.

A second approach to incorporate multiple channels is through concatenation of the ERP data in the subject dimension. The fMRI data is also replicated in the subject dimension so that the problem comes down to solving

$$\begin{bmatrix} \boldsymbol{X}^{fMRI} & \boldsymbol{X}^{EEG_1} \\ \boldsymbol{X}^{fMRI} & \boldsymbol{X}^{EEG_2} \\ \dots & \dots \\ \boldsymbol{X}^{fMRI} & \boldsymbol{X}^{EEG_n} \end{bmatrix} = \boldsymbol{A} \cdot [\boldsymbol{s}^{fMRI}\boldsymbol{s}^{EEG}] \quad (3)$$

This particular problem statement can be understood in analogy with (1). The signal matrix $\boldsymbol{X}$ now contains a number of signals that are equal to $subjects \cdot channels$. Seen from the original jointICA perspective, this corresponds to the situation of observing one channel, from a much larger number of subjects. ICA will decompose this variance-rich virtual channel using a large number of linked sources. The ERP peaks in these virtual sources can be regarded as originating from either one of the incorporated channels or from any combination of these channels.
For sake of simplicity, we refer to the jointICA with multiple time concatenated ERPs as tJointICA (2), and to the JointICA with subject concatenated ERPs as sJointICA (3).

4. RESULTS

As mentioned, first jointICA was applied to the EEG-fMRI data using the ERP data from one channel only to reproduce the results from [6], as they are considered the reference decomposition. Figure 2 shows one selected IC of the jointICA results for the ERP data from electrode PO8 and corresponding fMRI data. In total 18 joint components were extracted, since ICASSO showed that this would result in stable components.

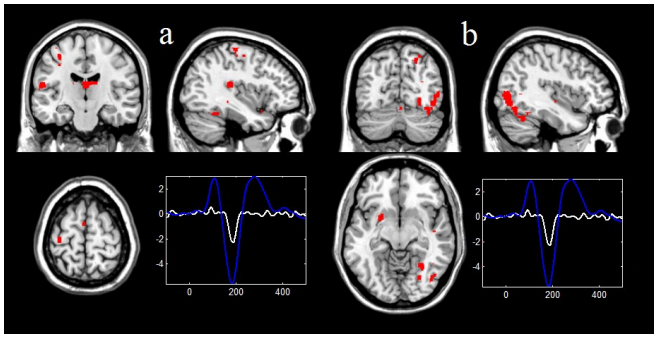


Fig. 2. One selected IC from jointICA results for channel PO8. The blue plot shows the grand average ERP for this channel, the white plot shows the ERP IC. fMRI IC activation maps are shown in red. a) Late N1 peak, showing the activations in motor and somatosensory areas. b) Same IC as in a), now showing the activations in visual areas. For all fMRI maps the same visualization threshold was used.

Figure 2a and 2b both show the same joint component correspond to the late N1 ERP wave, with each figure highlighting the activations in a different brain area. Figure 2a shows that the late N1 peak involves activations in the somatosensory and primary motor areas (Brodmann Area (BA) 1, 2, 3 and 4), in the supplementary motor areas (BA 6), and in the insula (BA 13). In Figure 2b the visual activations are shown, for example those in the right middle occipital gyrus (BA 19). When these activation maps discussed were compared with existing literature, it was indeed verified that the linking of these ERP and BOLD signals in the jointICA components do have a physiological resonance. To ease our further analysis, let us focus on these areas and call them our regions of interest (ROI's).

Figure 3 presents the first component of the decomposition when multiple ERP channels are incorporated in tJointICA. More specifically, we look at the case for 2, 3 and 5 electrodes, comprising of channels Oz and PO8 for the first, PO7, Oz and PO8 for the second and PO7, O1, Oz, O2 and PO8 for the third case. We call these different analyses 2tJointICA, 3tJointICA and 5tJointICA. In all scenarios, ICASSO advised 18 components.
Figure 3 shows the component, corresponding to the late N1 peak at electrode PO8, just as in the single electrode case. When comparing Figure 3a with the results from only one electrode in Figure 2a, we see that adding electrode Oz through concatenation in time results in highly similar fMRI maps. The ERP IC shows that these activation maps correspond to strong N1 activity at PO8 while the source is not active at Oz.
When looking at Figure 3b, we see that by adding also electrode PO7, some regions of interest are largely emphasized w.r.t. the single channel case. Primary and supplementary motor areas, somatosensory areas, and insula greatly light up.

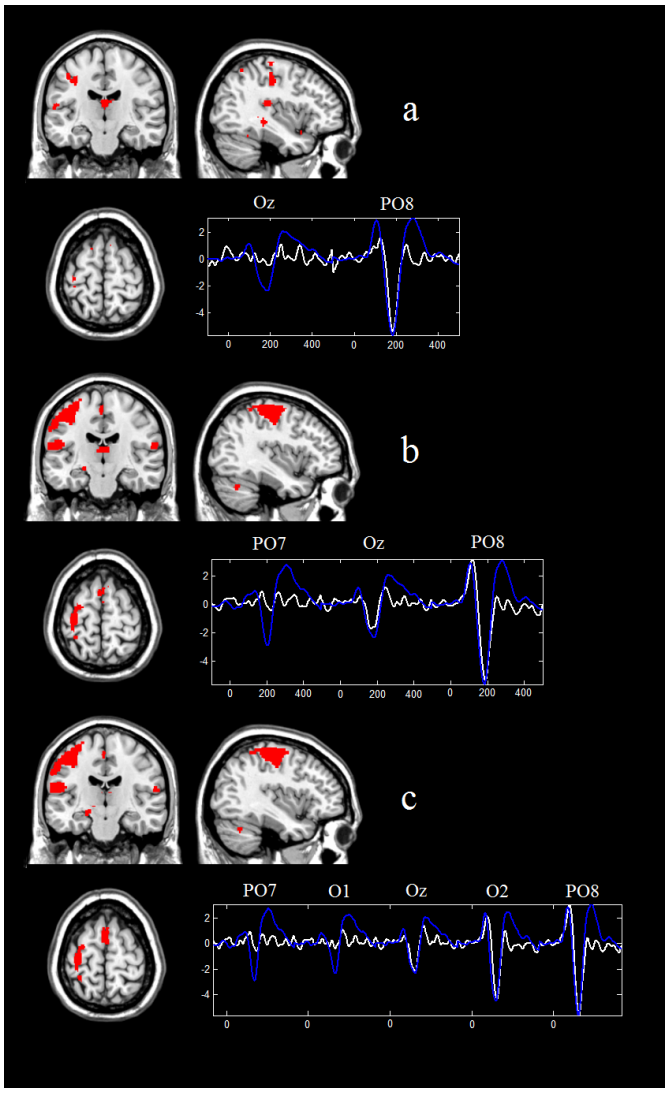


Fig. 3. JointICA results after concatenation of multiple channels in time dimension. Every time the first IC is shown. The blue plot shows the grand average ERP, the white shows the ERP IC. a) For channels Oz and PO8. b) PO7, Oz and PO8. c) PO7, O1, Oz, O2, and PO8. For all fMRI maps the same visualization threshold was used.

Finally, for the 5tJointICA, in the first joint component as shown in Figure 3c, we see the same clear activation maps as in Figure 3b, only now with the activity in the thalamic region almost gone. The ERP IC gradually shows more N1 activity closer to electrode PO8, which captures the correct lateralization of brain activity due to the stimulus in the down-left visual field quadrant.
A similar effect can be observed at other extracted components as well (not shown), i.e. the activation maps contain larger, more robust clusters.

The second method of incorporating multiple channels was to concatenate channels in the subject dimension. We inves-

tigate this by performing calculations for 2, (two sets of) 3 and 5 electrodes: including electrodes O2 and PO8 in the first case, Oz, O2 and PO8 in the second, PO7, Oz and PO8 in the third, and PO7, O1, Oz, O2 and PO8 in the fourth case, and referred to as 2s-, 3s-, and 5sJointICA. In these cases, ICASSO pointed out that the number of components should equal $18 \cdot number\ of\ channels$, which we complied to.

Figure 4 shows the extracted joint components for every case in this analysis, corresponding to a N1 peak. When comparing Figure 4a with the single-electrode case in Figure 2a, it can be seen that adding channel O2 in the subject dimension results in an ERP peak that is more compressed in time, and maybe slightly larger fMRI maps. When adding the channel Oz (Fig 4b), the result is an even more compressed ERP peak. The regions of interest are also clearly better visible. When choosing a different set of channels (PO7, Oz and PO8) which are wider apart, the fMRI areas change significantly to more compact areas, while the ERP IC stays approximately the same. Incorporating all five channels together gives a narrow ERP peak, which does not correspond to meaningful fMRI activity anymore.

When investigating other components extracted with sJointICA we see that for example the N1 peak of the single-channel case is subdivided in many different, narrower peaks. When looking at the activation maps, we see that the 2sJointICA in general gives better visualization of the regions of interest than the regular jointICA, and this is valid for all ERP components discussed in Figure 2. In some components captured by 3sJointICA excellent activation maps were obtained for these ROI's, while showing little other activations. However, in the 5sJointICA the ROI's could not even be identified, as lots of unknown activations were visible.

5. DISCUSSION

Although [8,9] showed that physiologically plausible decompositions can be obtained with single-channel jointICA this study shows the original jointICA can only tell one side of the story. The strength of jointICA is that components can be extracted that link activation in EEG to activation in fMRI, allowing to draw conclusions about where and when activity in the brain is processed. However, prior knowledge is always needed to select a channel of interest from the EEG and it is not excluded that spurious activations in fMRI become visible that has to be discarded by the same prior knowledge. As can be seen from Figures 3 and 4, incorporating multiple channel ERP data allows us to extract components which concentrate on certain other characteristics of the data under study, producing probably more robust results.

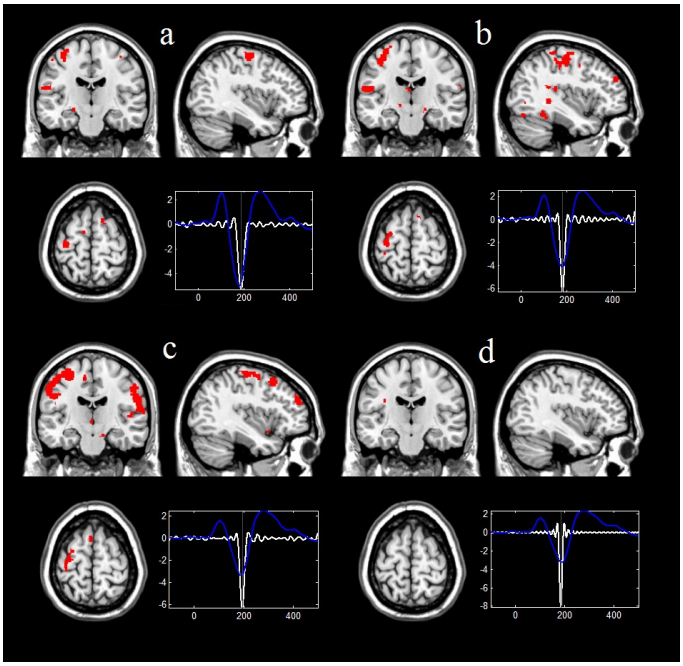


Fig. 4. JointICA results after concatenation of multiple channels in subject dimension. Every time the first IC is shown. The blue plot shows the grand average ERP, the white one shows the ERP IC. a) For channels O2 and PO8. b) Oz, O2 and PO8 c) PO7, Oz and PO8. d) PO7, O1, Oz, O2, and PO8. For all fMRI maps the same visualization threshold was used.

Figure 3 shows that the regions of interest obtained with tJointICA are in general larger compared with the results of the original jointCA. This could mean that this technique has a preference to show fMRI activations with a stronger physiological connection to the ERP peaks. However, by increasing the robustness, it has still to be determined that the method keeps its sensitivity to extract components related to small peaks like the P1.

The sJointICA results show that incorporating multiple channels in this way also allows putting the data in a different perspective. As explained above, sJointICA treats the channels incorporated as if they are originating from a common virtual channel. This arrangement of the data allows the extraction of a larger number of components. As shown by Figure 4, these components describe ERP characteristics that are very narrow in time. In this sense, the sJointICA sacrifices multiple channel information to obtain components with a finer time resolution. Figure 4a and 4c show us that this technique can result in components that allow certain fMRI areas of interest to be more clearly visualized, but that the choice of channel set also greatly influences which other areas light up or disappear.

Without having shown other components, we noticed during exploration that the sJointICA extracts many narrow IC's, which allow the study of the evolution of fMRI activations in nearly every time point present in the ERP. For example,

components corresponding to the early and small P1 were clearly visible for all three sJointICA decompositions discussed, and the fMRI maps were definitely physiologically relevant.

We clearly illustrate that incorporating multiple channels in the jointICA can lead to unraveling EEG-fMRI data with high spatio-temporal resolution. Several remarks are still in place. The first relates to the way we arranged the data. Always, higher dimensional data was compressed into a matrix, being subsequently decomposed. Recently, coupled matrix-tensor decompositions were proposed that potentially allow extracting components from the higher-dimensional EEG data in its original 3D representation and linking these to sources extracted from the fMRI. We explored such an approach, by decomposing the data with Coupled Matrix-Tensor Factorization (CMTF) [6,7]. However, up to now on our data, no convincing results were obtained although the underlying model is valid.

A second remark relates to the exploratory and illustrative nature of this study. For both tJointICA and sJointICA the choice of channels influenced the results in a major way. As the ultimate goal of a multimodal integration method is to derive new insights from new data, these influences should be further investigated for both approaches so that the methods can be used for exploratory purposes rather than post hoc validation studies. Further research is needed to develop a fully objective way of handling the different perspectives obtained with the different decompositions, and it needs to be further validated to what degree all components reveal physiological connections that could be of some diagnostic or functional value. Although we focused here on some regions of interest, this is a rather narrow approach, and it could even be that the most valuable information for physiological interpretability lies in the other activation areas, which varied among the different techniques and channel sets. Future research will certainly be conducted in an approach that is sensitive to new interpretations of these novel components.

6. CONCLUSION

In this paper we have explored the fusion of multiple channel ERP data and fMRI data. Different channels were concatenated in different ways into the classical jointICA formulation, and the extracted sources were analysed in terms of physiological plausibility. It was clearly shown that in many situations the extracted source activations showed more robust patterns than in the original jointICA. However, the large variability in the components extracted from different models need further investigation.

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