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EXPLORING THE EPILEPTIC NETWORK WITH PARALLEL ICA OF INTERICTAL EEG-FMRI

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ABSTRACT

The ultimate goal of the EEG-fMRI analysis in refractory focal epilepsy is the precise localization of the epileptogenic zone (EZ) to facilitate successful surgery. Many studies have shown that simultaneous EEG-correlated fMRI analysis can identify fMRI voxels which covary with the timing of interictal epileptic discharges (IEDs) assessed on EEG. However, this type of analysis often does not reveal a single focus but an extensive epileptic network. In this paper we investigate whether parallel independent component analysis (ICA), a data-driven, symmetric integration approach can disentangle this network. We assume that ICA of EEG and ICA of fMRI will reveal different temporal and spatial aspects of this network, respectively. We hypothesize that by matching these different epilepsy-related EEG and fMRI components, we can get a deeper insight in the neural processes this extensive network represents. We tested parallel ICA on 12 refractory epilepsy patients with good surgical outcome. Our results show that parallel ICA has an added value, as it can help the interpretation of the GLM results and pinpoint the EZ. Furthermore, it might help to understand how the various aspects of epileptic activity are reflected in EEG and fMRI.

Index Terms— ICA, parallel ICA, EEG, fMRI, epilepsy

1. INTRODUCTION

Refractory epilepsy patients continue to suffer from seizures despite of anti-epileptic medication. In focal epilepsy, where the seizures are generated in a certain confined brain region, surgical resection can offer a remedy. The resection or disconnection of the epileptogenic zone (EZ), by definition, is necessary and sufficient for seizure freedom. Simultaneous EEG-fMRI analysis was shown to be useful in the presurgical work-up of epilepsy [1]. Within the general linear model (GLM) framework, a regressor is defined based on the timing of the interictal epileptic discharges (IEDs) observed in the EEG. This regressor is then used to find voxels showing similar blood oxygen level dependent (BOLD) fMRI signal fluctuations. The GLM results often show widespread activations in the brain. Some studies claim that such widespread activations reflect multifocality, i.e. distributed epileptogenic tissue, while others argue that it reflects interregional interactions between the EZ and other remote sites, in line with the hypothesis that epilepsy is a network disorder [2].

Technically speaking, the mismatch between the temporal dynamics of EEG and fMRI limits the capabilities of GLM analysis. As the BOLD signal in response to a transient neural event peaks after several seconds, fMRI cannot differentiate the nuances of all underlying neural processes which are reflected in the millisecond resolution EEG. Therefore, the fine temporal details of EEG are lost in such a model-based approach. Alternatively, many studies applied independent component analysis (ICA) either to decompose EEG and define a more specific regressor for GLM [3,4] or to decompose fMRI and select the epileptic component based on IED timing information [5] or using machine learning in the absence of IEDs [6]. Such data-driven approaches efficiently exploit the entire underlying data structure. As a result, activation maps more specific to the EZ may be obtained. In this paper we propose a symmetric approach based on parallel ICA: we analyze both EEG and fMRI in a data-driven way to reveal different spatial and temporal processes in both modalities and then match the resulting components. This way we find multiple pairs of corresponding EEG-fMRI components. This will not only allow to pinpoint the EZ, but also to understand how various underlying epileptic processes are reflected in one modality and the other.

2. METHODS

2.1. Data acquisition and preprocessing

Simultaneously recorded EEG and fMRI data were acquired from 12 refractory focal epilepsy patients. All patients un-

derwent epilepsy surgery with good surgical outcome. EEG-fMRI data were recorded prior to surgery, but the results were not taken into account within the presurgical evaluation.

Functional images were acquired using a whole-brain single-shot T2* Gradient-Echo Echo Planar Imaging sequence in one of two 3 Tesla MR-scanners (Achieva TX with a 32-channel head coil and Intera Achieva with an 8-channel head coil, Philips Medical Systems, Best, The Netherlands); echo time = 33 ms, repetition time 2.2-2.5 s, voxel size: 2.6 x 3 x 2.6 mm^3. All fMRI images were realigned, slice-time corrected, normalized to MNI space using the coregistered high-resolution structural scan (resampled voxel size 2 x 2 x 2 mm^3) and spatially smoothed with an isotropic Gaussian kernel of 6 mm full width at half maximum using statistical parametric mapping (SPM8, Wellcome Department of Imaging Neuroscience, University College London, UK; available at `http://www.fil.ion.ucl.ac.uk/spm/`).

EEG data were recorded with a 24-channel or 32-channel MR-compatible EEG system while the patients rested with closed eyes. After offline bandpass filtering between 1-50Hz gradient artifacts and pulse artifacts were removed using the Bergen plug-in (Bergen fMRI Group,Bergen,Norway) and with Brain Vision Analyzer software (BrainProducts, Munich, Germany), respectively. Subsequently, IEDs were marked by a neurologist.

2.2. GLM-based analysis

EEG-correlated fMRI analysis was performed within the GLM framework. The timing of the most frequent spike type convolved with the canonical hemodynamic response function (provided in SPM8) was used as a regressor of interest. The six rigid-body motion correction parameters, the fMRI signal averaged over the lateral ventricles, and the signal averaged over a region within the white matter were included as confounding covariates. The activation maps were thresholded at $z > 3.5$ and only clusters containing at least 350 voxels were retained. These settings were shown to be the most sensitive ones to the EZ at 100% specificity [2].

2.3. Parallel ICA

EEG provides a volume conducted and spatially undersampled representation of a mixture of various independent neural processes. Similarly, these processes exhibit a spatially mixed and temporally degraded BOLD signal on fMRI. In order to disentangle the multiple sources of variability in each modality, ICA of EEG and fMRI is performed separately and then the sources are matched based on the similarity of their temporal fluctuations. This approach, called parallel ICA, has been applied in [7] to decompose multisubject EEG-fMRI data. Here, we apply it on a patient-by-patient basis. Furthermore, we adapted the matching procedure (see 2.3.3) to take into account the entire time span of the recordings instead of looking at only trial-by-trial fluctuations. The different steps of parallel ICA are explained in the following sections.

2.3.1. Temporal ICA of EEG

We assume that the multichannel EEG $X_{EEG} \in \mathbb{R}^{C \times T_{EEG}}$ observed over C channels and T_{EEG} number of time samples, is a linear mixture of N underlying independent source signals. Then, X_{EEG} can be written as follows:

$$X_{EEG} = A_{EEG} S_{EEG}. \quad (1)$$

The rows of the source matrix $S_{EEG} \in \mathbb{R}^{N \times T_{EEG}}$ contain the underlying sources, while the mixing matrix $A_{EEG} \in \mathbb{R}^{C \times N}$ describes the mixing system. In other words, each column of the mixing matrix describe the relative strength of a given source on each channel, i.e. the scalp topography of the source. The number of underlying components N was estimated as the median of the values obtained by the Minimum Description Length, Akaike and Bayesian Information Criteria. The independent components (ICs) were estimated using the Infomax algorithm [8].

2.3.2. Spatial ICA of fMRI

We assume that the BOLD signal fluctuations $X_{fMRI} \in \mathbb{R}^{T_{fMRI} \times V}$ observed over V voxels and T_{fMRI} time samples are generated by M independent sources which are organized independently in space:

$$X_{fMRI} = A_{fMRI} S_{fMRI}. \quad (2)$$

Here the rows of the source matrix S_{fMRI} represent the spatial maps, i.e. the organization of each source in the voxel space. The columns of the mixing matrix A_{fmri} describe the time course of each source, i.e. how the strength of their activity fluctuates over time. The decomposition was performed using The Probabilistic ICA algorithm provided in MELODIC, FSL toolbox (`http://fsl.fmrib.ox.ac.uk/fsl/fslwiki/`), including the automatic estimation of the number of ICs using a Bayesian framework.

2.3.3. EEG-fMRI component matching

First, the subset of epilepsy-related independent components (eICs) were selected as follows.

For EEG, a spike template was obtained by temporal averaging of the spikes marked by the neurologists. Averaging was time-locked to the largest negative peak of the spike. Then, the scalp topography at the largest negative peak was taken, along with the time course of the spike on the channel where this negative deflection was the largest. Similarly, an average IC spike was obtained by averaging the IC time course time-locked to the marked spikes. The topography of the ICs were obtained from the corresponding column of

Patient	EZ	GLM map	# EEG eICs	# fMRI eICs	# matches	Conclusive
1	RT	widespread	2 (9)	12 (97)	5	**Yes** EEG-eIC most similar to the template topography matches 2 fMRI-ICs with TL activation, one ipsilateral (r=0.2) and the other contralateral (r=0.11) to the EZ. The other EEG-IC matches with an RSN IC.
2	LT	LT activation	5 (8)	2 (103)	1	**Yes** Only fMRI-eIC67 has matched EEG-eICs. This map overlaps better with the EZ than the other fMRI-eIC.
3	LT	no activation	6 (8)	1 (68)	1	**Yes** The single fMRI-eIC overlaps with the EZ.
4	LP	widespread	4 (8)	1 (132)	1	**No** Single fMRI-eIC has occipital activation, not overlapping with the EZ.
5	RT	widespread	3 (4)	5 (86)	0	**No** No EEG-fMRI-eIC matches.
6	RTP	widespread	2 (5)	2 (60)	2	**No** Both EEG-eICs matched both fMRI-eICs, the network cannot be disentangled.
7	LT	LT activation	4 (8)	1 (48)	0	**No** No EEG-fMRI-eIC matches.
8	RF	widespread	6 (10)	3 (78)	2	**Yes** The EEG-eICs correlating best with the template topography match an fMRI-eIC overlapping with the EZ. Another EEG-eIC matches with a RSN fMRI-eIC.
9	LT	widespread	3 (7)	5 (50)	5	**Yes** The EEG-eIC which correlates best with the template topography matches fMRI-eIC3 which overlaps with the GLM activation maps at the EZ. fMRI-eICs with occipital activation are correlated to multiple EEG-eICs which reflect propagated activity (different topography or slow wave morphology with a late peak.)
10	LTO	no activation	3 (5)	5 (85)	3	**Yes** EEG-eIC most similar to the template topography matches with an fMRI-eIC reflecting the EZ. Other EEG-eICc which reflect propagated activity (slow wave morphology with a late peak or related to the secondary spike type) match fMRI-eICs reflecting other parts of the epileptic network remote from the EZ.
11	RT	no activation	4 (9)	1 (90)	1	**Yes** The single fMRI-eIC overlaps with the EZ.
12	LT	LT activation	6 (8)	7 (99)	6	**No** Interpretation is difficult, as the EEG-eICs are not very similar to the spike template. This is probably due to the fact that there were only 3 IEDs.

Table 1. True epileptogenic zone (EZ), GLM and Parallel ICA results of the patients. Next to the number of eICs the total number of ICs are indicated in brackets. Abbreviations: R: right L:left T: temporal F: frontal P: parietal O: occipital

the mixing matrix. Then, ICs which significantly correlated ($p < 0.05$, Pearson's correlation) both in time course and in spatial distribution with the spike template were labeled as epilepsy-related (EEG-eICs).

For fMRI, the spatial maps of the ICs were compared to the GLM activation maps, while the IC time courses were compared to the regressor of interest. ICs which showed significant correlation to the regressor ($p < 0.05$) and to the unthresholded activation maps ($p < 0.05$ and $r > 0.1$) were labeled as epilepsy related (fMRI-eICs). In the latter case constraining the correlation coefficient was necessary, because significance at $p < 0.05$ was easily reached due to the large number of voxels ($n > 5 \cdot 10^5$). Afterwards, the fMRI spatial maps were normalized to z-scores by subtracting the mean voxel value and dividing with the standard deviation and were thresholded at $|z| \leq 5$. The selected fMRI ICs were visually inspected and those containing a majority of suprathreshold voxels in the ventricles or in the white matter were rejected.

Subsequently, the epilepsy related EEG and fMRI components were matched based on their time courses. In order to account for the difference in their temporal dynamics the time courses of the EEG ICs were convolved with the canonical hemodynamic response function and the time courses of the fMRI time courses were upsampled to match the sampling rate of the EEG. Then, Pearson's correlation coefficient $r_P$was computed for all possible EEG-fMRI IC pairs. A match was established if $r_P > 0.1$.

3. RESULTS

Results obtained using GLM-based analysis and parallel ICA are summarized in Table 1. The GLM activation map showed a single activation cluster overlapping with the EZ in 3 out of 12 cases. In 6 cases it showed activation both in the EZ and

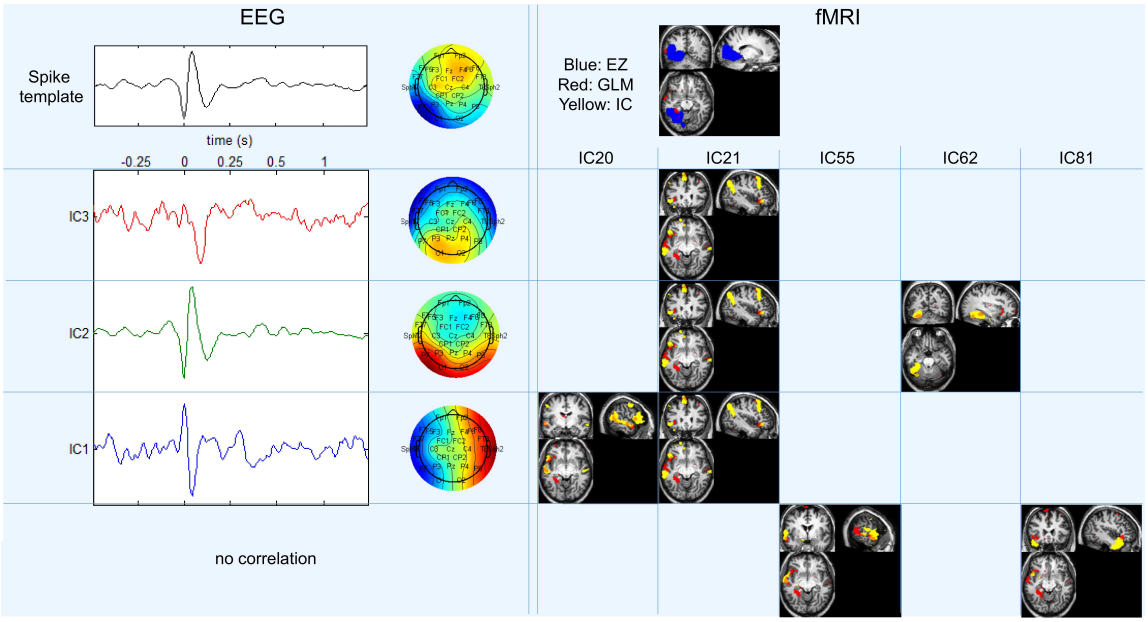


Fig. 1. The epileptic network of patient 10. The spike template, the EZ and the GLM activation map are shown on the top. Note that none of the GLM clusters exceed 350 voxels threshold, we nevertheless show them for comparison with the IC maps. The epilepsy related EEG and fMRI components are shown on the right and on the left, respectively. The matching EEG and fMRI components are aligned horizontally. In case an fMRI IC matched multiple EEG ICs, it is shown in all the corresponding rows. fMRI ICs with no matching EEG component are shown in the bottom row.

in one or more remote areas. Finally, in 3 cases no significant activation was present.

Multiple epileptic EEG-eICs were found in all cases. A single fMRI-eIC was found in 4 patients and multiple fMRI-eICs were found in 8 patients. Parallel ICA found a matching EEG-eIC for a single fMRI-eIC in 4 cases. In 3 out of these 4 cases (patients 2, 3 and 11) this fMRI-eIC overlapped with the EZ. In 6 further patients parallel ICA found a matching EEG-eIC for at least 2 fMRI-eICs. In patient 12, although the objective criteria did select matching eIC pairs, the interpretation of these results is not reliable. Based on visual assessment, none of the EEG-eICs were similar to the spike template. This might be due to the fact that only 3 IEDs were present during this recording, which is too few to be reliably extracted by ICA. No matching IC pairs were found in patients 5 and 7. In patient 8 both EEG-eICs matched both fMRI-eICs, therefore, this result does not allow to disentangle the different parts of the network. In the remaining 4 cases (patients 1, 8, 9 and 10) the EEG-eIC most similar to the spike template in topography matched that particular fMRI-eIC which overlaps with the GLM map in the EZ. Other EEG-eICs which were less similar to the spike template matched an fMRI-eIC overlapping with the GLM map in a region remote to the EZ. In summary, while GLM revealed focal activations in only 3 cases, parallel ICA could reveal the EZ in 7 cases. Although the results were inconclusive in 5 patients, in 4 of them they were not misleading either.

In order to illustrate our findings on a concrete case, we show the epileptic network of patient 10, as revealed by parallel ICA in Figure 1. This patient had 3 epileptic EEG and 5 epileptic fMRI components. The second epileptic EEG component (EEG-IC2) is most similar to the spike template both in its time course and its topography. EEG-IC1 resembles the secondary spike type of this patient over the temporal area, while EEG-IC3 shows a deflection a few milliseconds later than the mean spike peak. Therefore, EEG-IC2 can be associated with onset type activity, while EEG-IC1 and EEG-IC3 can be associated with propagated activity. Each of these 3 ICs have a matching fMRI component. EEG-IC2 matched to fMRI-IC62 and fMRI-IC21. While fMRI-IC62 was matched exclusively to EEG-IC2, fMRI-IC21 matched with both propagated EEG ICs as well. Finally, EEG-IC1 matched fMRI-IC20. From this one can deduce that fMRI-IC62 represents the onset region of the epileptic activity, while the fMRI-IC20 and fMRI-IC21 are involved at a later phase of epileptiform activity. Notably, the spatial map of fMRI-IC62 coincides best with the zone of surgical resection which rendered the patient seizure free.

4. DISCUSSION

Our results showed that parallel ICA can help the interpretation of the extensive GLM activation maps in the following way. In case a single EEG-fMRI-eIC pair is selected, the spa-

tial map of the fMRI-IC correctly indicated the EZ. In cases where multiple EEG-fMRI-eIC pairs were found, the fMRI-eICs can be interpreted based on their EEG-eIC pairs. Those fMRI-eICs which matched exclusively the EEG-eICs most similar to the spike template overlapped with the GLM map at the EZ (type 1 EEG-fMRI eICs). Other EEG-eICs which were less similar to the spike template matched an fMRI-eIC overlapping with the GLM map in a region remote to the EZ (type 2 EEG-fMRI eICs). The significance of this finding is twofold. First, it shows that the parallel ICA approach can help in the objective identification of the EZ and facilitate successful surgical resection and seizure freedom. Moreover, parallel ICA may shed the light on different mechanisms underlying the epileptic network activity. Type 1 EEG-fMRI eICs can be interpreted as electrographical and BOLD correlates of primary, onset-type epileptic activity. The spatial maps of type 2 EEG-fMRI-eICs were often similar to well-known resting state networks (RSNs). Notably, many recent studies have shown that RSNs are impaired in epilepsy patients. The characteristics of the type 2 EEG components were somewhat heterogeneous. In some cases they were similar to the secondary spike type of the patient, while others reflected a slow-wave like morphology, i.e. less sharp than the spike template and with a later occurring peak. Interestingly, such slow waves in epilepsy are associated with inhibitory mechanisms or propagated activity. The existence of type 2 EEG-fMRI-eICs suggest that slow waves might be the electrographical correlates of the same neuronal processes which cause an altered RSN activity in epilepsy patients.

The proposed parallel ICA-based approach has some limitations. The matching procedure was restricted to EEG-eICs and fMRI-eICs selected based on the spike template in EEG and the GLM results. However, there might be epilepsy related potential fluctuations which are not time-locked to the spike occurrences, or might be better characterized in frequency than in time domain [4]. Moreover, we took into account only the spike template which corresponds to the most frequent spike type, while in patients 5, 7, 10 and 12 an additional spike type was present. Except for patient 10, the parallel ICA results were not satisfactory, suggesting that the epileptic activity is more complex and requires more involved analysis in these cases. Similarly, there might be impaired networks in areas different from the GLM activation clusters. Such aspects of epileptic activity are hidden from our methodology. Moreover, parallel ICA decomposes EEG and fMRI independently from each other. Other data fusion approaches, like jointICA [9, 10] or joint matrix/tensor factorizations [11, 12] could decompose EEG and fMRI simultaneously, facilitating mutual information flow between the modalities within the decomposition. Although this implies the very strong assumption of both modalities sharing the same linear mixing system, they might provide results complementary to parallel ICA.

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