

# An ICA based method to process simultaneous EEG-fMRI in Epilepsy

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## INTRODUCTION

Simultaneous EEG-fMRI is becoming a common tool in the study of epilepsy due to its great clinical potential on the localization of the sources of interictal epileptiform activity. One of the questions that remains unanswered, however, is how to characterize the different spikes and bursts of interictal activity that are to be convolved with the hemodynamic response function (hrf) to be used as a model for the event related design.

In this study, Independent Component Analysis (ICA) of the EEG data was evaluated as a potential blind method to characterize the spikes, bursts of spikes or of slow waves with different amplitudes and durations. The core mathematical concept of ICA is to minimize the mutual information among the data projections. It simply attempts to find a coordinate system in which the data projections have minimal temporal overlap. ICA are already a popular means to remove artifacts such as eye blinks, eye movement or muscular activity (1). Because of the high amplitude of interictal activity, and the fact that its sources can generally be considered static, it is expected to prove useful on the separation of interictal activity.

## METHODS

Studies were performed using a 32 channel MRI compatible EEG system (from Micromed), and 1.5T MRI scanner (Siemens Symphony). The EEG acquisition was performed at 2048Hz. Structural images were acquired using an MPRAGE sequence. Images were acquired in a 256×256×104 matrix with a resolution of 0.5×0.5×1mm<sup>3</sup>. The functional studies were carried out using echo planar imaging (EPI) with the following parameters: TE=40ms; BW=1698 Hz/Px; TR=2.480, flip angle=85, with matrix dimensions of 64×64×24 and a resolution 3×3×5mm<sup>3</sup>. Three runs of approximately 15 minutes (360 volumes) were performed for each patient.

Four patients who had been reported to have a very high rate of interictal spike activity in previous monitoring studies were selected for this study. Of those four patients, only two had interictal activity during the functional studies. In one of the two patients only two EEG-fMRI runs could be processed due to EEG malfunction during the last run.

The EEG data was postprocessed using a Matlab toolbox, EEGLAB (2). First gradient related artifacts were removed (using a Gaussian-weighted mean artifact) (3), followed by the detection of the QRS complex and removal of the cardiobalogram artifact using algorithms developed by Niazy *et al.* (4). The EEG data was then bandpass filtered (1 to 60 Hz), and down sampled to 128Hz. ICA decomposition of the data using an infomax function (1) was performed and the components related to spikes or bursts, as identified by an epilepsy expert neurophysiologist, were selected for further analysis.

Three event related models were considered: (a) A model based on the spikes, slow waves and bursts as identified by the neurophysiologist, characterized as a block with the length of the interictal activity and a fixed amplitude of 1; (b) A model based on one or two ICA components that most strongly contribute to the interictal activity. This model only considers the absolute amplitude of the signal that deviates over three standard deviations from the mean of the component of interest; (c) A third model results from multiplying the two previous models, which presents the advantages of removing any undesired noise present in the component, and having a more accurate description of the amplitude of the activity. These various models of neural activity were then convolved with a hrf to obtain the hemodynamic time course model, and the functional data were then processed using FEAT (FMRI Expert Analysis Tool; FMRIB's Software Library). Higher-level analysis was carried out using a fixed effects model, by forcing the random effects variance to zero in FLAME (5). Z-statistic images were thresholded at  $Z>3.0$  and a (corrected) cluster significance threshold of  $P=0.01$ .

## RESULTS

Fig. 1 shows an example of ICA decomposition of the EEG signal. The first ICA component is highly correlated with the interictal activity and was used for the fMRI processing. In Fig. 2 it is possible to observe, as well as a good agreement, the increased significance and size of activated regions when using the interictal related ICA component to model neural activity. The volume of the statistically most significant cluster that was obtained with either of the methods ((a)  $Z_{max}=5.7$ , (b)  $Z_{max}=7.2$  and (c)  $Z_{max}=5.5$ ), was 4.4 times larger with method (b) then with method (a). The same qualitative agreement and increased significance was observed in the second patient where two ICA components were used. One showed significant positive Z-values, whilst while the other showed significant negative Z-values (6).

## CONCLUSIONS AND FUTURE WORK

These preliminary results indicate that this methodology could increase the detectability of sources of interictal activity, as well as to reduce the time needed to create the event related model. Future research should be aimed at developing new approaches to model neuronal activity, starting from the ICA component.

**References** (1) Makeig S., et al, *Proc Natl. Acad. Sci. U.S.A.* (1997), **94**, 10979-84; (2) Delorme A, et al., *Journal of Neuroscience Methods*, (2004), **134**, 9-21; (3) P.J. Allen, et. al., *NeuroImage* **12**, 230-239 (2000); (4) Niazy et. al., *NeuroImage*, **28** (2005) 720-737; (5) Woolrich M.W., *NeuroImage* **14** (2001)1370-1386; (6) Stephanovic B. et al., *Neuroimage* **28** (2005) 205-215.

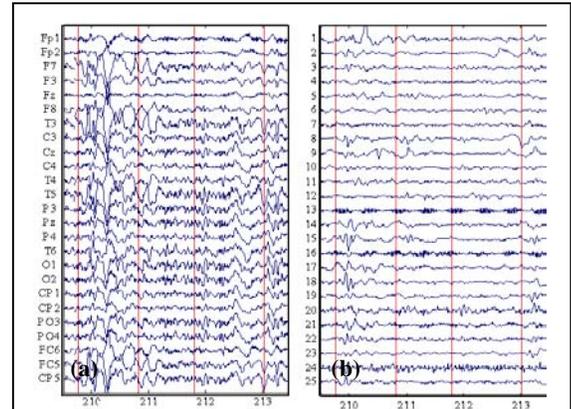


Fig. 1(a) A segment of EEG, acquired synchronously with fMRI after gradient cardiobalogram artifact removal. Interictal activity is visible at 210s; (b) The EEG signal decomposition into its various ICA components.

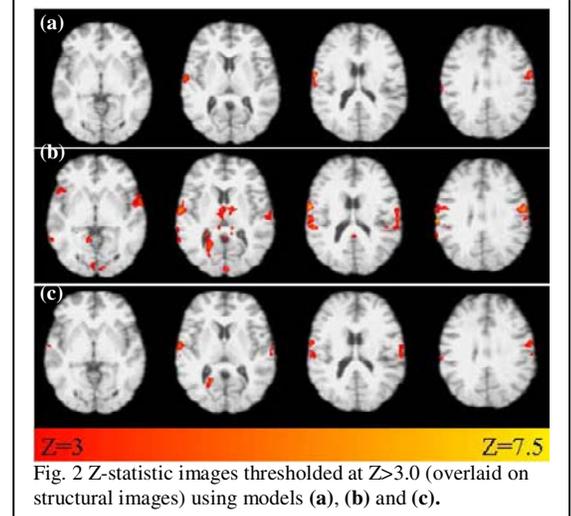


Fig. 2 Z-statistic images thresholded at  $Z>3.0$  (overlaid on structural images) using models (a), (b) and (c).