GENERALIZED EEG-FMRI SPECTRAL AND SPATIOSPECTRAL HEURISTIC MODELS

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ABSTRACT

The aim of the current study is visualization of task-related variability in EEG-fMRI data, performed as a blind-search analysis without stimulus timings, using a methodology that is based on Kilner's et al. heuristic approach [2]. We show that filters of the relative EEG spectra with different frequency responses visualize different task-related brain networks. The effect is more pronounced within an event-related oddball paradigm (i.e. detecting rare visual targets) than within a block-design semantic decision paradigm (i.e. detecting semantic errors). The mutual information between different EEG-fMRI activation maps calculated with filters of different frequency responses appears stable between the different paradigms. We also introduce preliminary results implementing the heuristic analysis with spatiospectral EEG components, where the filter response has two dimensions and depends on frequency and channels.

Index Terms**—** Simultaneous EEG-fMRI, heuristic model, GLM, ICA

1. INTRODUCTION

In the current study we extended current models used to analyze simultaneously measured EEG-fMRI signals. The ultimate goal of work was to reconstruct task-related networks from EEG-fMRI data without prior knowledge of stimulation timing (see also [1-3]).

Recently, we proposed that relative (i.e. normalized) EEG power [$p(\omega)$, eq. 1] is more powerful than absolute power for visualizing task-related EEG-fMRI networks [1]. The strongest task-related correlates between relative EEG power and fMRI-BOLD [4] signal were observed within the α (8-12Hz) and γ (20-40Hz) bands.

$$p(\omega) = \frac{s(\omega)}{\int s(\omega)\, d\omega} \tag{1}$$

In eq. 1, $s(\omega)$ represents the power spectral density for frequency ω in the acquisition time duration of the *n-th* fMRI scan. The numerator and denominator fluctuate over time, sometimes asynchronously across frequencies.

Kilner et al. [2] introduced the EEG-fMRI heuristic model in 2005 (eq. 2). This approach fuses the data based on models of trans-membrane voltage and current changes, i.e. directly at the level of neuronal changes.

$$\left[\frac{\tilde{b}}{b}\right]^2 \propto (1+a)^2 \propto \frac{\int \omega^2 \tilde{p}(\omega) d\omega}{\int \omega^2 p(\omega) d\omega} \tag{2}$$

This simplest model declares that changes in BOLD signal b are proportional to neuronal activation a which is proportional to changes in root mean square frequency of whole normalized (relative) EEG power spectrum $p(\omega)$. The character ~ indicates variables during increased activity, while variables without ~ represent signal values during rest.

Rosa et al. (2010) [3] considered the denominators in equation (2) to have a constant baseline, and incorporated general linear model (GLM) fitting (eq. 3).

$$\tilde{b} \propto \sqrt{\int \omega^2 \tilde{p}(\omega) d\omega} \tag{3}$$

Fig. 1 shows the function ω^2 (in eq. 3) is only different frequency response of the relative EEG spectra filter in contrast to the response of a band of interest.

In our previous study [1], we calculated task-related activation maps for different frequency bands of interest, sug-

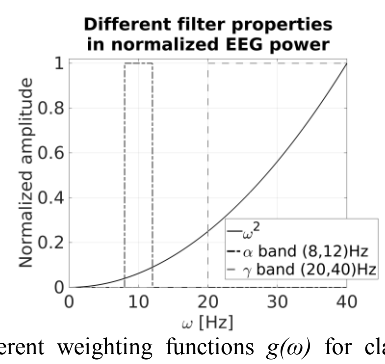

Fig. 1. Different weighting functions $g(\omega)$ for classic heuristic model and different frequency bands of interest

gesting that, the equation 3 can be extended and multiple filtering weighting functions $g(\omega)$ can be derived (eq. 4) for visualization of different task-related networks. In the current study we aim at evaluating the applicability of this statement. First, we assess if different weighting functions can allow visualizing different task-related networks. Secondly, we determine whether the effect is stable across two tasks with different stimulation paradigm (event-related versus block design).

$$\tilde{b} \propto \sqrt{\int g(\omega)\tilde{p}(\omega)d\omega} \tag{4}$$

Equations (3) and (4) are limited since they apply the same weighting functions, irrespective of their scalp spatial location. Therefore, we propose the novel spatiospectral heuristic approach, where the filtering weighting function $g(c,\omega)$ depends on both frequency ω and channel c (eq. 5), i.e. utilizing the full scalp coverage of EEG.

$$\tilde{b} \propto \sqrt{\iint g(c,\omega)\tilde{p}(c,\omega)\, dc\, d\omega} \tag{5}$$

We thus describe how eq. 5 can be implemented within the spatiospectral group independent component decomposition by Bridwell et al. (2013) [5] for $g(c,\omega)$ estimation and we present preliminary results obtained using such approach. Results of both generalized approaches (eqs. 4, 5) are also compared with classic heuristic model (eq. 3).

2. METHODS

2.1 Stimulation paradigms

2.1.1. Visual oddball task (VOT)

The VOT is an event-related paradigm where subjects detect rare visual targets. The experiment is frequently used to visualize fronto-parietal visual attention networks. Further details (and analysis of the same dataset) are described in our previous work [1].

2.1.2. Semantic decision task (SDT)

The SDT was designed as a block-designed stimulation paradigm with the goal of eliciting robust activation of the language network. During the probe condition, two types of sentences were presented in random order. Sentences with semantic error created by the phonemic exchange (e.g. The cat was chased by **f**og) alternated with semantically correct sentences. Strings of ‘X’ or ‘O’s were displayed during control condition. Subjects were asked to push a button held in the right hand when they detected erroneous sentences or a string of ‘O’s.

42 healthy subjects (18 women, age 25±5, 2 left-handed men) were scanned with a 1.5T Siemens Symphony MR scanner. Parameters of fMRI acquisition were: 230 scans, TR = 1850ms, TE = 40ms, FA = 80°, voxel size = 3.9 x 3.9 x 6 mm^3, no gap between slices, 20 transversal slices. The field of view covered supratentorial regions.

Simultaneously, scalp EEG data were recorded with a 30-electrode MR compatible EEG system (*BrainProducts, Germany*). ECG were recorded to remove physiological artifacts from EEG. Signals were sampled at 5 kHz with 0.5µV resolution for EEG, and 10µV for ECG.

High-resolution anatomical T1-weighted MPRAGE images were acquired (160 sagittal slices, matrix size 256 x 256 resampled to 512 x 512, slice thickness = 1.17mm, TR = 1700ms, TE = 3.96ms, FOV = 246mm, FA = 15°).

2.2. fMRI and EEG data preprocessing

The fMRI data were preprocessed with SPM8 (*Wellcome Trust Centre for Neuroimaging, London, UK*) software library. Motion artifacts were minimized by alignment of all functional scans, followed by co-registration with subject’s anatomical image and normalization into standardized space (MNI). Functional scans were spatially smoothed with a 3D Gaussian filter. Periods longer than 128s were cut off.

The raw EEG data were corrected for the gradient artifacts and down-sampled to 250Hz. Cardiac artifacts were suppressed by mean artifact subtraction using BrainVision Analyzer 2.0 (*BrainProducts, Germany*) for all previous steps, followed by band-pass filtering from 1Hz to 40Hz.

2.3. Analysis of EEG-fMRI data

For the visual oddball task, group activation maps from our previous study [1] were used for comparison with the classic heuristic model.

For VOT and SDT datasets, the selected 1st level single subject analysis setting was: averaging across all 30 electrodes of interest, temporal weighting of power periods corresponding to repetition time of fMRI scanning (TR), and these frequency bands of interest for relative power (δ: 0-4Hz, θ: 4-8Hz, α: 8-12Hz, β: 12-20Hz, γ: 20-40Hz) (for more details see Methods in [1]) or classic heuristic model approach (eq. 3). EEG regressors were convolved with the canonical hemodynamic response function (HRF) [4].

One-sample t-test was used to analyze the data at a group level as previously reported for the frequency bands of interest approach [1]. GLM estimations and 2nd level group statistics were calculated with SPM8 software.

The similarity of group activation maps was validated for VOT and SDT based on unnormalized mutual information [6] coefficients (MICs) characterizing their joint entropy as in [1].

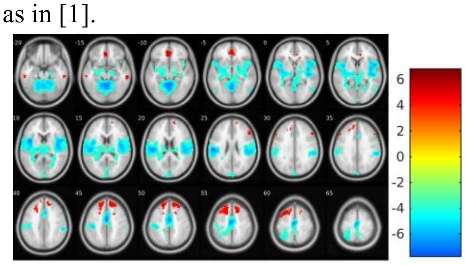

Fig. 2. Group activation map for heuristic model from visual oddball task data (p<0.001 unc.)

2.3. Spatiospectral weighting function in heuristic model

Bridwel et al. (2013) [5] presented group spatiospectral independent component decomposition of EEG signal. Within EEG, they focused on resting-state absolute power fluctuations. Since we have reported that absolute power is not able to visualize task-related networks [1], we used relative power instead. Bridwell's et al. approach was used to calculate a two-parameter filtering weighting functions $g(c,\omega)$ which depend on the spatial position of channel c and frequency ω (eq. 5).

In eq. 5, $\tilde{p}(c,\omega)$ is equal to the Bridwell's et al.'s input power spectrogram in time t [5] *in normalized (relative) form.* The filtering weighting function $g(c,\omega)$ is then equal to Bridwell's et al.'s output independent spatiospectral component [5]. 50 of 256 spatiospectral EEG components were used after principal component (PCA) decomposition. Then, data were separated at 20 independent components with 10 icasso [7] runs implemented in the GIFT toolbox [8]. Timecourses of those EEG components were compared with fMRI. For preliminary results, the EEG components were compared with the BOLD signal in GLM for VOT data.

3. RESULTS

VOT group activation maps for all relative power in different frequency bands of interest were published here [1]. The group-averaged VOT map for the heuristic model is shown in Fig. 2. Based on visual inspection, the VOT heuristic model based activation map is the most similar to the relative power γ band VOT activation map. Such observation is consistent with the fact, that both filters reach maximal gain in the same frequency range 20-40Hz (Fig. 1). Activated supra-thresholded sensory-motor cortices are truly contralateral to the right-handed pushed button on target stimuli. Heuristic model and relative γ band are non-sensitive to activated visual cortex areas detected with relative δ and bands. Any model did not visualize fronto-parietal network.

Based on visual inspection for block-designed SDT, the final supra-thresholded group activation maps (shown in Fig. 3 for 2 different slices) appear less sensitive to the frequency band of interest as it is for VOT maps [1]. Beside relative θ band, all other bands and heuristic model could visualize the stimulated visual network, found to be negatively correlated with fMRI analysis without EEG on same dataset. Beside those areas, supra-thresholded activations were found in areas that were not related to the task (venous sinuses, insula) with 5 of 6 approaches. Only noise was above the threshold for the θ band. We did not find activations in stimulated speech cortices (Broca's and Wernicke's areas), found to be positively correlated with fMRI analysis without EEG on same dataset

The similarity of different EEG-fMRI maps is assessed with MIC (Table 1, Table 2). Linear trend in joint histograms starts to be obvious at MIC above 0.75 [1] (highlighted in Table 1, 2). MIC between relative δ and α bands, as well as between classic heuristic model and relative γ band show high MIC in both tasks, suggesting that they represent similar EEG responses.

Preliminary results of the spatiospectral heuristic model on VOT data are shown in Fig. 4. 50 selected components after PCA explains in average about 90% of explained variability in EEG relative power (Fig. 4a). The higher α band and its 2nd harmonics (lying in area of γ band) is shown as one independent $g(c,\omega)$ function of eq. 5 (Fig. 4b). The spatial distribution of group EEG-fMRI map (Fig. 4c) visualizes activations in sensory-motor cortices, detected less lateralized than for classic heuristic approach (Fig. 2) and relative γ band [1].

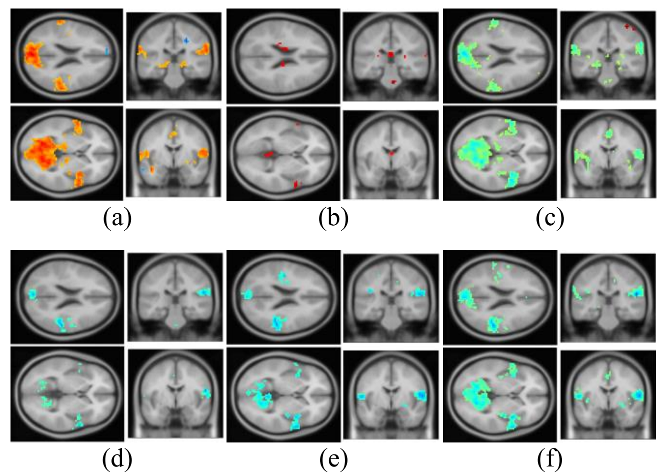

Fig. 3. Group-averaged activation maps for semantic decision task in slices $[-63\ -28\ 22]_{MNI}$ and $[-60\ 4\ 2]_{MNI}$ between the BOLD signal and **(a)** relative δ band; **(b)** relative θ band; **(c)** relative α band; **(d)** relative β band; **(e)** relative γ band; **(f)** heuristic model (p<0.001 unc.)

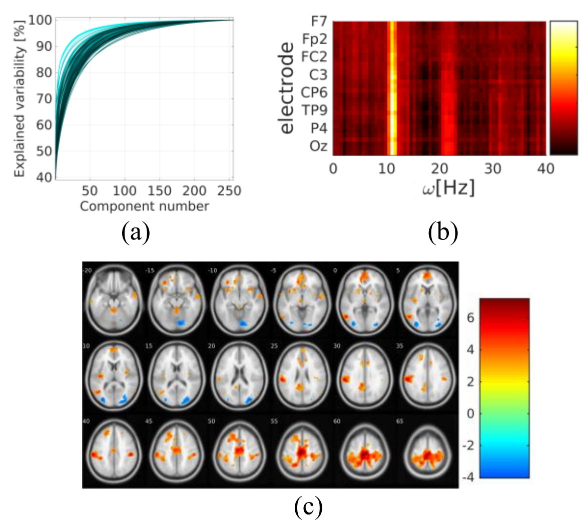

Fig. 4. Spatiospectral heuristic model results at visual oddball task data; **(a)** Cumulative explained variability of relative EEG power after PCA; **(b)** One selected independent spatiospectral EEG component; **(c)** Group-averaged activation map (p<0.005 unc.) between fMRI and the EEG component

Tab. 1. Unnormalized MICs between group EEG-fMRI activation maps for visual oddball task estimated with relative power in different frequency bands or with classic heuristic model

δ	θ	α	β	γ	HM	
4,28	0,49	**1,10**	0,48	0,48	0,70	**δ**
	4,26	0,70	0,33	0,38	0,64	**θ**
		4,56	0,43	0,43	0,65	**α**
			3,88	0,45	0,51	**β**
				4,32	**0,98**	**γ**
					4,45	**HM**

Tab. 2. Unnormalized MICs between group EEG-fMRI activation maps for semantic decision task estimated with relative power in different frequency bands or with classic heuristic model

δ	θ	α	β	γ	HM	
4,46	0,21	**0,89**	0,56	0,52	0,72	**δ**
	4,11	0,30	0,26	0,26	0,27	**θ**
		4,49	0,48	0,44	0,58	**α**
			4.24	0,49	0,65	**β**
				4,32	**1,29**	**γ**
					4,40	**HM**

4. DISCUSSION

4.1 Advantages and limitations

Although MIC matrices contain the same pattern for both tasks, SDT maps seem to be more similar across different frequency bands (Fig.3). This may be due to either the greater robustness of the block-design paradigm, or differences between the two tasks.

Although the lateralization was reduced, spatiospectral EEG decomposition was able to more specifically separate sensory-motor activations into one separate component with less widespread activation maps (Fig.4c) relative to classic heuristic model (Fig. 2) and relative γ [1]. To overcome these limitations, the data fusion process will have to be still optimized, e.g. identifying of optimal impulse response function reflecting the relationship between EEG and fMRI-BOLD data will be necessary, as it has been done for resting-state data previously [5]. Still the main advantage of this method (eq. 5) is that it may provide more precise visualization of task-related (sensory-motor) network without other task non-related areas, as it happens for approaches utilizing principles described by eq. (3) or eq. (4). In addition, the EEG spectra may be decomposed into a greater number of frequency bands in a data-driven manner.

4.2. Importance for biomedical applications

Simultaneous EEG-fMRI measurement has a great potential for localizing epileptogenous foci. Several studies used manual temporal detection of spikes in EEG, followed by fusion with fMRI data for identifying epileptic foci, e.g. [9]. These methods are rarely automatized, limiting their interpretability and reliability. The present approach may be useful for identifying and removing spatiospectral patterns in EEG, while retaining spikes. From this point of view, EEG-fMRI fusion based on EEG spectra has a great potential for automatic detection of epileptogenous focus.

5. CONCLUSION

Our results showed that the classic heuristic model approach overlaps with the relative γ band approach for visual oddball and semantic decision tasks. The evaluation of different frequency related spectral patterns (application of eq. 4) seems to be more meaningful for the event related visual task than for the block design semantic paradigm. Overall equation (5) has the potential to be a promising approach for extracting unique information from EEG when conducting joint EEG-fMRI analysis, since it increases the spatial specificity of EEG-fMRI task activations (as evaluated on oddball task).

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