fMRI Motion Regressors Based on EEG Motion Artifacts in Simultaneous EEG-fMRI

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INTRODUCTION: The common approach to correction of head motion effects in fMRI data involves head volume registration, e.g. [1], and the use of the resulting six motion parameters as nuisance regressors in the general linear model (GLM), e.g. [2,3]. However, significant head motions occurring on time scales shorter than the fMRI repetition time *TR* cannot be adequately sampled and taken into account. This reduces accuracy of fMRI results for subjects exhibiting large head motions, including children, patients with mental disorders, and even healthy controls engaged in demanding tasks. EEG performed simultaneously with fMRI with millisecond temporal resolution is particularly sensitive to rapid head rotations. Motion artifacts in EEG-fMRI recordings contain useful real-time information about such rotations. Here we describe a novel and simple approach for deriving additional fMRI motion regressors directly from EEG motion artifacts, and demonstrate its efficiency for patients with major depression.

METHODS: The proposed approach is based on an assumption that motion artifacts measured by each EEG electrode can be expressed as a result of a rotation of an effective contour on the surface of the head in the uniform magnetic field of the scanner. This contour (of unknown but constant size and shape) includes a given EEG electrode and the reference electrode, as well as relevant EEG leads and paths of ionic scalp conductivity. Because voltage (emf) induced in a contour due to its motion in the field is proportional to a time derivative of the magnetic flux, time integration yields scalar product $\mathbf{n}_0\cdot(\mathbf{n}(t=0)-\mathbf{n}(t))$, where $\mathbf{n}_0$ is a unit vector along the field, and $\mathbf{n}(t)$ is a unit normal vector of the contour at time t. This quantity can be viewed as a "motion parameter" describing orientation of the contour as a function of time. Thus, integration of EEG motion artifacts for a set of EEG channels yields a set of "motion parameters". An independent components analysis (ICA) applied to EEG recordings allows decomposition of the channels' waveforms into independent components (ICs). The ICs reflecting major head rotations can be easily identified by visual inspection of their time courses, as well as their topographies, which are typically bipolar (Fig. 1a). The ICA also allows separation of large head rotations from instrumental noise and spurious signal fluctuations in EEG data. The selected and integrated ICs can be interpreted as (unitless) real-time measures of the most independent head rotations. They can be downsampled to *TR* and used as GLM motion regressors in addition to the six motion parameters.

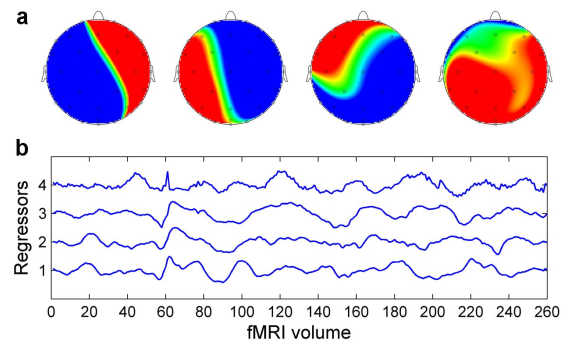

Fig. 1. a) Topographies of EEG independent components reflecting major head rotations of a single subject; b) their time courses after time integration and downsampling to match the fMRI time course.

Three MDD patients (two females) underwent a resting EEG-fMRI scan lasting 8 min 40 s. The measurements were performed on a General Electric Discovery MR750 3T MRI scanner with an 8-channel head coil array. A single-shot gradient echo EPI sequence with FOV/slice=240/2.9mm, *TR/TE*=2000/30ms, SENSE=2, image matrix 96x96, flip=90°, 34 axial slices, was employed for fMRI. A 32-channel MR-compatible EEG system (Brain Products GmbH) was used for simultaneous EEG recordings in 0.016−250 Hz band with 0.1 µV resolution and 5 kS/s sampling rate. All three patients exhibited significant head movements during the resting scan (the maximum displacements in brain masks were 2.2 mm, 1.6 mm, and 2.8 mm, respectively). The fMRI data were processed in AFNI [4]. The EEG data processing was performed using Brain Products' Analyzer 2, and included correction of MRI and cardioballistic artifacts. The FastICA algorithm [5] with 20 ICs was then applied, and four ICs were selected, integrated, downsampled to match the fMRI time course, and used as GLM motion regressors. The GLM analysis of the fMRI data (bandpass filtered between 0 and 0.1 Hz) included a regressor of interest (time course of a 12 mm diameter ROI in the posterior cingulate region), the six motion parameters, five polynomial terms, and (optionally) the four EEG based motion regressors.

RESULTS: Fig. 2a exhibits the percent reduction in the standard deviation of the GLM fit error time course, obtained after inclusion of the four EEG based motion regressors in addition to the six fMRI motion parameters. The results are averaged over the three subjects. The average change in the GLM fit error std for gray matter is −10%...−5%, with stronger effects in the frontal and occipital regions, more affected by head motions. Note that the GLM fit errors in a single-subject analysis at time points exhibiting significant head motions could be reduced by up to 50%, as illustrated in Fig. 2b.

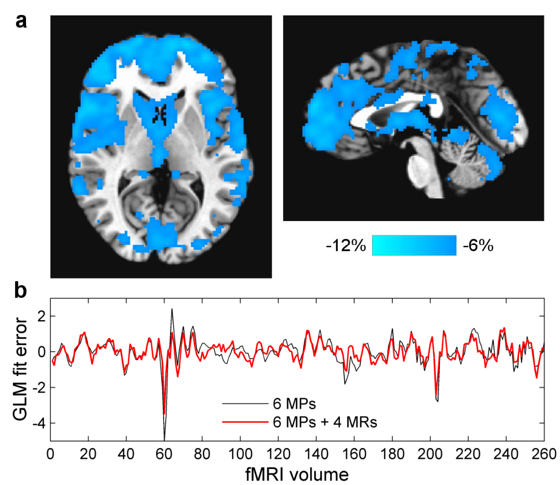

Fig. 2. a) Average reduction (%) in std of the GLM fit error after inclusion of the EEG based motion regressors; b) the GLM fit error time course for a selected ROI in a single-subject analysis.

CONCLUSION: The proposed approach makes it possible to generate additional motion regressors for analysis of fMRI data based entirely on motion artifacts in concurrent EEG recordings. We expect that the efficiency of this method can be improved further if the EEG based real-time motion regressors are used to correct raw fMRI data prior to volume registration and slice timing adjustment. In this case, the ICs corresponding to cardioballistic artifacts in EEG data can also be efficiently employed.

REFERENCES: [1] A. Jiang et al. *HBM* **3**, 224 (1995). [2] K.J. Friston et al. *MRM* **35**, 346 (1996). [3] T. Johnstone et al. *HBM* **27**, 779 (2006). [4] R.W. Cox & J.S. Hyde. *NMR Biomed*. **10**, 171 (1997). [5] A. Hyvarinen, *IEEE Trans. Neural Netw*. **10**, 626 (1999).