EXPLORING EEG MICROSTATES AS ELECTROPHYSIOLOGICAL SIGNATURES OF BOLD RESTING STATE NETWORKS

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INTRODUCTION: Neuroimaging research suggests that in the awake, resting behavioral state, cerebral function is driven by large-scale functional networks of neuronal activity. The results of BOLD fMRI studies more specifically reveal spontaneous, large-amplitude, low-frequency (<0.1Hz) fluctuations that are temporally correlated and spatially organized into several functional networks referred to collectively as resting state networks (RSNs) [1,2]. However, the neurophysiological basis of these BOLD RSNs is not fully understood. Moreover, it remains unclear whether the slow fluctuations of RSNs at durations of ~10 s reflect faster neuronal dynamics at the sub-second level. Previous studies have explored the band-limited power of electrophysiological recordings, such as EEG. The data from these studies, however, indicated that RSNs are related to oscillations in a wide range of frequency bands rather than to oscillations in specific band. In the present study we explored EEG microstates, which do not rely on any single frequency band, as RSN correlates. To facilitate this research we developed a novel, fully data-driven approach to analyze microstates, and then applied this method to reveal specific electrophysiological signatures for a range of RSNs.

METHODS: Simultaneous resting-state EEG and fMRI data were acquired from nine healthy human subjects (age 33 ± 10 years; one female). The experiments were performed on a General Electric Discovery MR750 3T MRI scanner with an 8-channel receive-only head array coil. For the whole brain fMRI, a single shot gradient echo EPI sequence with Sensitivity Encoding (SENSE) and FOV/slice thickness/gap=220/2.9/0.2mm was used (*TR/TE*=2000/30ms, acceleration=2, image matrix 64x64, flip=30° [3], 34 axial slices). High-density EEG signals from 126 channels were simultaneously recorded with BOLD fMRI scans using MRI-compatible BrainAmp MR Plus amplifiers (in 0.016−250 Hz band with 0.1 μV resolution and 5000 Hz sampling rate). Three closed-eye resting scans, each lasting six minutes and ten seconds, were acquired for each subject. A pneumatic respiration belt and a photoplethysmograph were used to obtain respiration and pulse oximetry measurements, respectively. Using similar configurations, concurrent EEG and respiration waveform data were recorded separately (on different days) in three of the nine subjects in a mock MRI scanner, which provided a dark and quiet non-magnetic environment resembling the visuospatial aspects of MRI.

A new method was developed to analyze microstates using independent component analysis (ICA). After correcting the EEG recording for the gradient and ballistocardiac artifacts associated with MRI scanning, the EEG topographies at the local peaks of global field power were subjected to ICA and decomposed into independent components (ICs), which were considered as the main microstates. The same decomposition matrix was applied to the continuous EEG, resulting in time courses of ICs. At each time point, a main microstate was ascribed based on which IC has the maximum absolute intensity value. The time courses of microstates were convolved with a canonical hemodynamic response function and down-sampled to TR. The preprocessed fMRI data were subjected to group spatial ICA in order to extract BOLD RSNs. The correlation between time courses of microstates and RSNs were assessed. Microstates were also used as regressor in a general linear model (GLM) to identify areas where BOLD activity co-varied with the time courses of microstates and then compared to the BOLD RSNs.

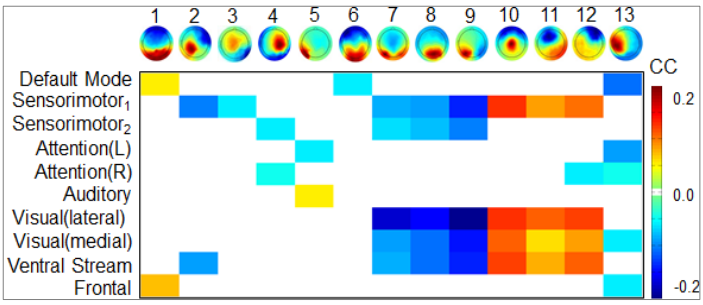

Figure 1. Correlation between thirteen EEG microstates and ten RSNs

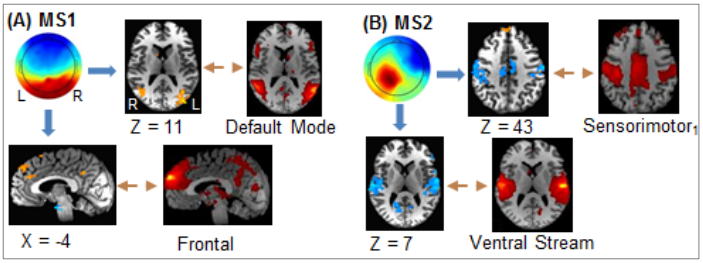

Figure 2. BOLD activations identified by EEG microstates (blue arrows) and compared to RSN activations identified from fMRI data (brown arrows)

RESULTS: Thirteen main microstates were identified at the group level, which were consistent with those identified at the single subject level from EEG recordings both inside and outside of the scanner. Ten RSNs were extracted from group fMRI data as consistent with previous report [4]. The correlation matrix between time courses of microstates and RSNs revealed that each microstate was associated with one, two, or a combination of several RSNs (Fig. 1). Among the thirteen microstates, MS1-6 are correlated to only one or two RSNs, collectively including sensorimotor, auditory, attention, frontal, ventral stream and default mode networks. MS7-12 share similar profile in regard to the RSNs, mostly the visual and sensorimotor networks. As opposed to MS1-12, MS13 is related to a wide range of RSNs. The BOLD activations identified by microstates using GLM to a large extent approximate the spatial distributions of corresponding RSNs that were separately derived from fMRI data alone (Fig. 2).

DISCUSSION: Here we developed a novel and fully data-driven approach for extracting independent microstates from high-density EEG data. We then compared the temporal dynamics of these microstates to fluctuations in the resting state networks measured in simultaneously acquired, whole brain fMRI data. Our approach differs from previous work studying microstates in the way that our method extracted microstates by maximizing their temporal independence instead of based on their similarity of spatial topographies [5]. Independent microstates allow identifying multiple distinct RSNs, which otherwise would not be delineated from correlated microstates. Our results show for the first time that a wide range of RSNs, including visual, sensorimotor, auditory, attention, frontal, ventral stream and default model networks, can be identified by corresponding microstates.

REFERENCES: [1]Biswal B. et al. Magn Reson Med **34**,537,1995; [2]Fox M.D. et al. Nature Rev. Neuroscience **8**,700, 2007; [3]Gonzalez-Castillo J. et al. Neuroimage **54**,2764, 2011; [4]Damoiseaux et al. J.S. et al. Proc. Natl. Acad. Sci. **103**,13848, 2006; [5]Britz J. et al. NeuroImage **52**,1162, 2010.