Tracking Dynamic Resting-State Networks with High Temporal Resolution fMRI

H-L. Lee[1], B. Zahneisen[1], T. Grotz[1], P. LeVan[1], and J. Hennig[1]
[1]Medical Physics, University Medical Center Freiburg, Freiburg, Germany

Introduction Resting-state fMRI detects spontaneous BOLD signal fluctuations when no specific cognitive task is being performed [1]. Common resting-state network analysis methods look for coherent signal changes in the time-series, with the underlining assumption that those networks are stationary during the scan session (typically ranging from 5 to 15 minutes). Chang *et al.* showed that the variation in functional connectivity could occur within a smaller time scale [2]. Regular whole-brain resting-state fMRI protocol uses echo-planar imaging (EPI) with TR around two seconds. With this sampling rate, several minutes of signal has to be recorded before there are enough data points in the time series for connectivity or component analysis. The low temporal resolution makes it difficult to detect faster fluctuations of functional networks.

In this study we used a highly under-sampled single-shot concentric shells trajectory [3] to shorten the acquisition time and increase temporal resolution. A TR of 100 ms was achieved, which provided us reasonable amount of data points to calculate functional connectivity in a 20 seconds time window. We applied a sliding window on the resting BOLD time series to track the dynamics in selected networks.

Methods Resting-state fMRI data from three healthy volunteers were acquired on a 3.0 T Siemens Trio scanner (Siemens Healthcare, Erlangen, Germany). Subjects were instructed to look at a cross on a projected screen and relax during the scan session. The concentric shells acquisition scheme with TR = 100 ms was used to collect 4096 time frames (total scan time 6 min 50 sec, first 30 sec discarded). Imaging volume had an FOV of 256 × 256 × 240 mm^3. All post-processing was done in MATLAB (The Mathworks, Inc., Natick, MA). A 64 × 64 × 48 image matrix was reconstructed using the forward operator evaluated with a non-uniform FFT (nuFFT) algorithm, based on coil sensitivity weightings and measured gradient trajectory.

Rigid-body motion correction and spatial smoothing was performed in SPM8 (http://www.fil.ion.ucl.ac.uk/spm). Global signal regression was also applied to reduce non-neural signal correlations [4]. Signals were then filtered to isolate 0.01~0.1 Hz component. We applied a sliding window (width = 20 seconds/200 samples, step = 2 seconds, 180 frames in total) on the time series, with manually selected seeds for visual and sensory-motor networks, and an iterative correlation calculation [5]. Final correlation maps were converted to z-maps using fisher's z-transform, and the variance in each voxel along the time axis was calculated. The time-frequency energy distribution of each network was obtained using fast Fourier transform and the same sliding window. Connectivity strength was calculated as the average of voxel correlation coefficients within a network.

Results & Discussion Figure 1 shows sample frames of (a) visual (b) sensory-motor networks in one representative subject. The images in the far left column are the coherent networks in the whole time series (6 min 20 sec long). The 7 columns in the middle are the networks found with 20 seconds of signal each, starting at t = 0, one step 50 seconds apart. Colored maps at the right are the variance in z-value throughout the 180 frames. Figure 2 contains the signal time-frequency functions of both networks during the whole scan. The energy distribution is clearly not stationary over the course of a single session. The average connectivity strength of both networks also varies between 0.4~0.7 during the 6 min 20 sec scan.

Using a single-shot concentric shells trajectory, we have demonstrated the identification of resting-state networks with a temporal resolution of 20 seconds. The high sampling rate enables us to track the changes of functional networks during a multiple-minutes long fMRI scan. The optimal parameters for the sliding window are yet to be determined with further studies. The trade-off between temporal resolution and correlation analysis stability has to be carefully considered when choosing the length of the time window. Nevertheless, combining a fast acquisition and sliding window scheme can potentially allow us to observe dynamic network reconfiguration of the rapidly switching human brain activities.

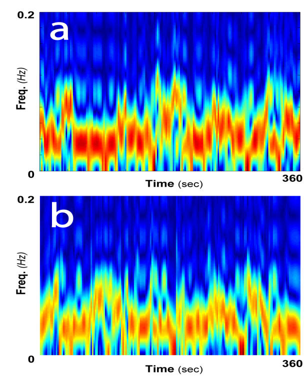

Figure 2 Time-frequency plot of the average signals in (a) visual (b) sensory-motor networks.

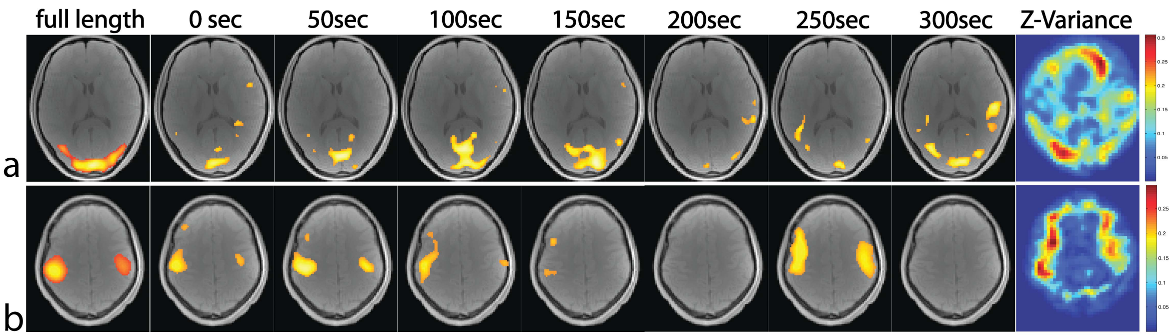

Figure 1 Coherent networks at (a) visual (b) sensory-motor cortex, obtained at different time points during one scan session. Each correlation map was calculated with a 20-second time window, starting at t = 0/50/100/150/200/250/300 sec.

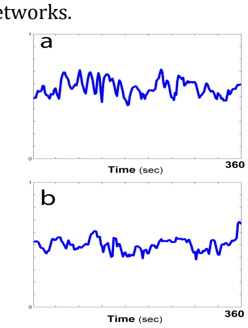

Figure 3 Connectivity strength within (a) visual (b) sensory-motor networks as functions of time.

References [1] Biswal *et al.*, MRM 34: 537–541; [2] Chang *et al.*, NeuroImage, 50:81-98 (2010); [3] Zahneisen *et al.*, ISMRM 2011 (submitted); [4] Hampson *et al.*, Hum. Brain Mapp. 15, 247-262 (2002); [5] Lee *et al.*, Proc. ISMRM 2010, pp.3493.