Forty Weeks of Rest: An Investigation into Functional Network Stability

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Background & Introduction: Despite the growing popularity of BOLD resting-state functional connectivity MRI (rsfc-MRI)[1-4], the intra-subject inter-session reproducibility of rsfc-MRI outcome measures has not yet been well established, although some reports have appeared with modest number of repeat scans[5-6]. Determining the intra-subject stability of resting-state networks would be important for their use in longitudinal studies, inter-group comparisons, and individual assessments, e.g., for surgical planning. We report on rsfc-MRI data acquired in a single participant over forty weekly sessions.

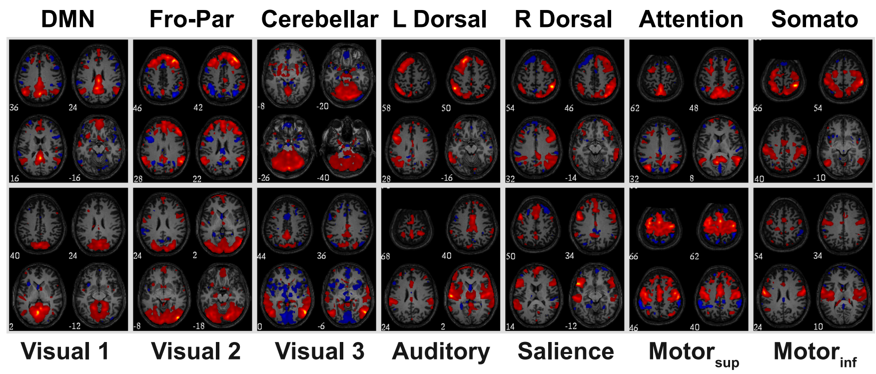

Figure 1: The 14 functional networks.

Methods - Data Acquisition: Late every Thursday morning for forty weeks, a participant underwent a session at 3.0 Tesla (Philips HealthCare) that included a 6 min 40 sec long rsfc-MRI scan. BOLD fMRI data of the whole brain were acquired using multislice SENSE-EPI, with TR/TE=2000/30 ms, flip angle = 75°, and 37 slices of an 80 x 80 matrix giving a nominal spatial resolution of 3x3x3 mm^3 plus a 1 mm slice gap.

Methods - Data Analysis: Preprocessing comprised slice-time correction, motion correction, unified segmentation, spatial normalization, smoothing with a 6 mm FWHM Gaussian kernel, and voxel-wise linear detrending. Spatial independent component analysis (ICA) using temporal concatenation[7] of all sessions' data was performed using GIFT[8]. Automatic dimensionality estimation using minimum descriptor length resulted in 36 components; based upon their spatial distributions and time course frequency distributions, 14 components were retained as functional networks, while the others were discarded as nuisances induced by, e.g., head motion, respiration, and cardiac pulsations. For the 14 networks, single-session maps and time courses were back-reconstructed[7]. The η^2, a measure of spatial similarity[9], of each session's spatial map with respect to the corresponding aggregate map, was calculated. The root mean square (RMS) of each network's time course was computed for each session. Between-network connectivity (BNC)[10,11] was computed for each session between pairs of networks, as the Pearson correlation coefficient of the network time courses.

Results: The 14 functional networks are depicted in Figure 1. Inter-session variation in their spatial distributions (assessed via resemblance to each network's aggregate map, using η^2) and time course fluctuation amplitude (assessed using RMS) are shown in Figure 2 and 3, respectively. Mean BNC values are shown in Figure 4. The kite-tail structure of the BNC matrix suggests a categorization of cerebral networks into three classes: exteroceptive (attention, somatosensory, motor, visual and auditory networks), default (default mode network (DMN) and fronto-parietal network) and dorsal streams (right and left dorsal stream networks). Similar spatial and temporal stability measures were observed within each network class with the default and the dorsal stream networks more consistent (η^2 $p<0.043$; RMS $p<0.039$) than exteroceptive networks.

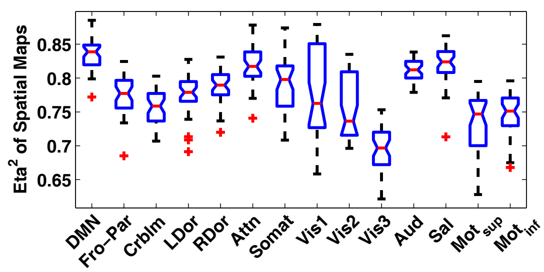

Figure 2: Spatial similarity of networks across sessions. "Box & whisker" plots show median (red bar), inter-quartile range (blue boxes), 1.5 times inter-quartile range (black lines), and outliers (red cross

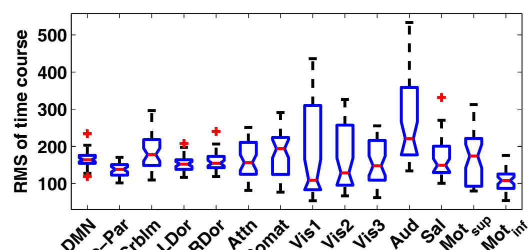

Figure 3: Similarity of network time course fluctuation amplitude across sessions.

Discussion and Conclusions: Spatial ICA of rsfc-MRI data acquired from one subject weekly over 40 weeks yielded 14 functional networks. High values of η^2 provide evidence that network maps are stable, consistent with previous reports using low repeat measures[5,6]. The most stable network was the DMN; the most variable were the three visual networks. A classification of functional networks, using BNC, into three classes yields two observations: First, default networks were more stable than exteroceptive networks. Second, default networks were more connected to one another than to exteroceptive networks; similarly, exteroceptive networks were more connected to one another than to default networks. Because the default networks were more stable, they may be better suited for the detection of changes due to disease, while the more variable exteroceptive networks may be better suited for correlational studies exploiting network variability.

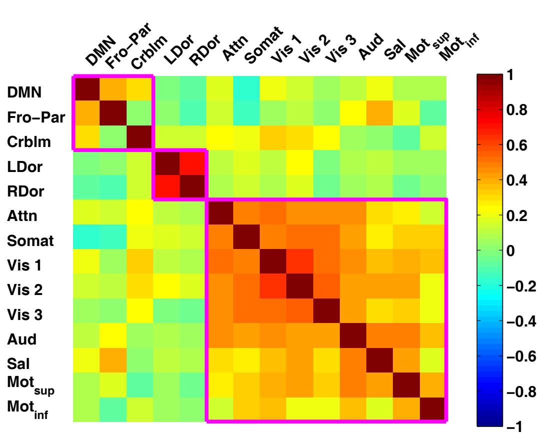

Figure 4: Between-network connectivities. Magenta lines show clustering of networks.

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