Grading resting-state fMRI datasets by reweighted L1 regression

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Introduction

During the resting state of brain, a large number of brain areas show spontaneous neuronal activities. The resting-state fMRI (rsfMRI) detects the dynamic neuronal activity using a long series of BOLD imaging. It measures the "connectivity" of brain functional areas using either correlation analysis or independent component analysis[1]. RsfMRI is rapidly emerging as powerful tools for in vivo mapping of intrinsic connectivity networks (ICNs) [2]. However, in our experiences, rsfMRI sometimes shows unstable results even if we preform studies using the same imaging protocols and data analysis methods. Therefore, it is highly desirable to develop a method to grade rsfMRI datasets. In this study, we proposed to use reweighted L1 regression, a form of robust regression, to find the "outliers" of the rsfMRI time series in the default-mode network (DMN) and developed a grading method for rsfMRI datasets.

Material and Methods

Four rsfMRI datasets were acquired on a 3T whole-body MR scanner using a gradient-echo EPI sequence (TR/TE: 2000/30ms, matrix size: 64x64, 33slices parallel to AC-PC, 200 measurements). The subjects were instructed to remain awake and not to think of anything in particular. The obtained datasets were analyzed using MATLAB. Preprocessing of rsfMRI data, including motion correction, image filtering, and normalization, was performed using SPM8 (http://www.fil.ion.ucl.ac.uk/spm). Then, a correlation analysis was applied using a seed point centered in posterior cingulate cortex (PCC, 27 voxels, MNI coordinates = -3, -54, 27) to explore DMN. The voxels with correlation coefficient (CC) higher that 0.7 were selected for the subsequent L1-regression analysis. The intensities of PCC and each selected voxels obtained at the same time formed a pair (x, y) (x: PCC intensity, y: voxel intensity). The pairs (x, y) were filled into matrices for a weighted first-order L1 regression as follows:

$$\hat{A}_l = \arg\min_A \| W_l (Y - XA) \|_1$$

where A contains the polynomial coefficients (a slope and a intercept) , W is the weighting matrix, and (X, Y) are the matrices formed by data pairs. After L1 minimization, a "weighting" was obtained for each time point of each voxel. In reweighted L1 regression, a data pair with a relatively low weighting is most likely an outlier of the data group. Our processing algorithm generated an index called outlier-count (OC) which counted total time points of voxels with weightings lower than preset thresholds.

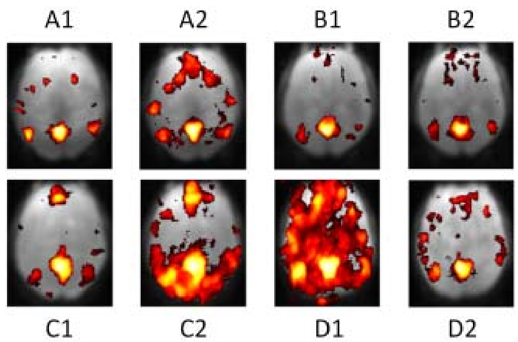

Figure 1 The resting-state maps obtained from four volunteers (A, B, C, D). A1 - D1 are reconstructed from measurement 1- 100 and A2 - D2 are reconstructed from measurement 101 – 200. Notice that C2 and D2 clearly exhibit different from the rest 6 maps.

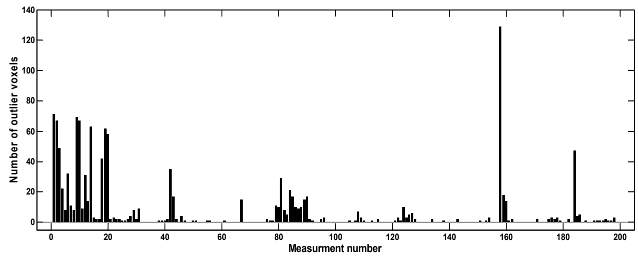

Figure 2: The total outlier voxels corresponding to measurement numbers for subject D. Weighting threshold = 0.6

Results

Figure 1 displays rsfMRI maps of the four volunteers (denoted as A, B, C, D). Due to limited space of the abstract, we demonstrate the rsfMRI maps using maximum intensity projection along head to foot direction. Two maps for each subject are reconstructed using measurements 1-100 (denoted as A1, B1, C1, D1) and 101-200 (denoted as A2, B2, C2, D2), respectively. The OC values obtained using weighting threshold of 0.5, 0.6 and 0.7 are listed in Table 1. From the resting-sate maps, we found C2 and D1 exhibits differently compared to the rest 6 maps. The mean OC values of {C2, D1} and {A1, A2, B1, B2, C1, D2} are (threshold of weighting: OC values, 0.5: 61, 0.6: 719.5, 0.7: 2731) and (0.5: 10.33, 0.6: 80.6, 0.7: 494.5), respectively. Figure 2 shows the distribution of outlier voxels corresponding to measurement numbers. Notice that a substantial amount of outlier voxels distributed in measurement number 1 to 20 and 80 to 90. The distribution of outlier voxels is consistent with the finding in rsfMRI maps (D1 and D2).

Table 1. The OC values obtained using different weighting thresholds

threshold	A1	A2	B1	B2	C1	C2	D1	D2
0.7	15	3	110	560	1215	1751	3711	1064
0.6	1	0	2	27	175	438	1001	278
0.5	0	0	0	0	4	53	69	58

Discussion and conclusions

This study developed an index called outlier-count to grade resting-state fMRI datasets. Reweighted L1 regression was utilized to find outliers in the rsfMRI maps. In the maps that are visually different from the known DMN (C2 and D1), the OC values are significantly higher than those obtained from the rest 6 datasets. We empirically found that OC value calculated using weighting threshold of 0.6 seems more sensitive than those calculated using weighting threshold of 0.5 and 0.7. This method is potentially useful to determine corrupted data of the whole time series. During resting-state fMRI experiment, this method could also serve as a quick quality-control index. The improper data may be caused by various reasons (e.g., motion, being asleep or brain activity other than the "resting-state"). The major weakness of this study is that the improper datasets (C2 and D1) are determined according to the authors' experiences. Further study should be conducted to develop a more specific criterion of a corrupted dataset. In conclusion, the preliminary results of this study demonstrate the OC index obtained using reweighted L1 regression is a promising method to grade a resting-state fMRI dataset.

Reference

[1] Biswal, B., et al. 1995, MRM 34.537541 [2] Greicius, M.D., et al. 2004, PNAS [3]Chang C. et al. 2010, NeuroImage