Online model-free detection of fMRI signals: Application to task activation and resting state functional connectivity

S. Peltier[1], S. LaConte[1], X. Hu[1]

[1]Biomedical Engineering, Emory University/Georgia Tech, Atlanta, GA, United States

INTRODUCTION

Online detection methods have been applied to detect task activation in functional MRI [1-2], but typically use a cumulative correlation with a known reference waveform. Low frequency (< 0.08 Hz) synchronized oscillations in resting state timecourses have been detected in recent fMRI studies [3-4]. These fluctuations are important as a potential signal of interest, which could indicate connectivity between functionally related areas of the brain. It has also been shown that the synchronized oscillations decrease in some spontaneous pathological states (such as cocaine injection) [5,6]. Thus, detection of these functional connectivity patterns may help to serve as a gauge of normal brain activity. Currently, functional connectivity detection is applied only in offline post-processing analysis.

In this work, we apply an online clustering algorithm to detect both task-related activation and low frequency resting state functional connectivity in real time. This allows both the online model-free detection of activation, and expands connectivity analysis to allow online detection of "resting state" brain networks.

METHODS

Acquisition

A series of fMRI experiments were performed on a 3 T Siemens Trio scanner. An EPI pulse sequence was used to acquire 280 images, with two 5 mm thick axial slices acquired in each run, with an in-plane resolution of 3.4 mm^2. Pulse sequence parameters were TR/TE/FA/FOV of 750 ms/35 ms/50°/22 cm. Two subjects were studied under conditions of rest and activation. Two sets of resting-state and activation data were acquired for each subject. A bimanual finger-tapping motor paradigm (20s fixation, 20s task, 5 repeats) was implemented for the activation data. Resting state data was acquired while the subjects were inactive (lying still, with fixation cross being presented), with a scan time of 200 seconds. Paradigm cues were presented to the subject in Presentation (Neurobehavorial Systems, Albany, CA) connected to a back projection screen.

Online clustering

A dynamic k-means algorithm was implemented in the Siemens Image Calculation Environment (ICE) to cluster the data in real time. The k-means algorithm was implemented for its computational efficiency, and ability to classify fMRI data [7]. The iterative algorithm grouped the data from each slice into nine clusters, as follows. The ICE program first reconstructs the slice data. The slice timecourses (in memory) are updated to have zero mean and unit variance. The current slice data are then clustered by the k-means algorithm to the closest exemplars (using the squared Euclidean metric), and the exemplars updated. This step is repeated until convergence (no change in exemplar classification for any timecourse). The final cluster maps for each TR are then written out and displayed for online viewing at the scanner console. For the resting state connectivity, a moving average of ten timepoints was used to low-pass filter the data before processing by the algorithm.

Analysis

The resultant cluster maps were examined for significant activity in the anatomically defined motor regions, for both the task and resting state data, as a function of time. For comparison, task activation and functional connectivity maps were generated in offline post-processing. Task activation maps were formed by correlating the slice data timecourses with the task paradigm. Functional connectivity maps were then formed by using a seed ROI in the dominant motor cortex, defined as the four contiguous voxels having the highest activation. The timecourse of this ROI in the resting-state data was then averaged together, and low-pass filtered < 0.08 Hz. This low frequency reference was then correlated with the low-pass filtered resting state data to form functional connectivity correlation maps. This is a common method for examining resting state functional connectivity [1-3, 8-9].

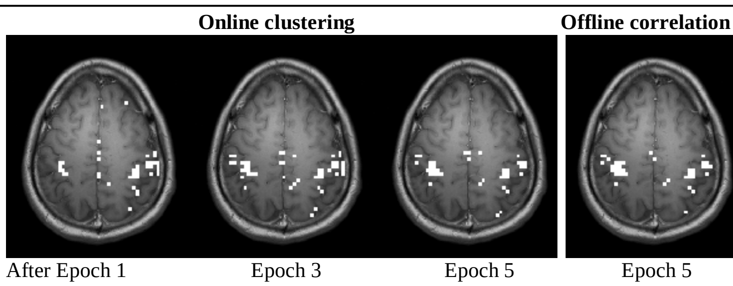

Figure 1. Comparison of online clustering with offline correlation for bilateral motor task with five cycles. The number of activated voxels of the correlation map is matched to the last cluster result (equivalent to $t > 6.7$).

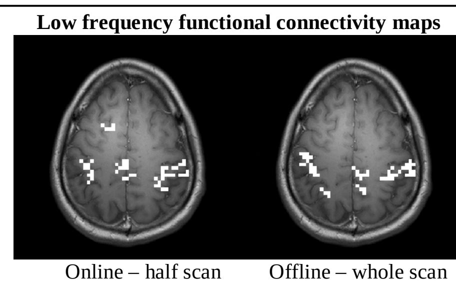

Figure 2. Comparison of online and offline low frequency functional connectivity maps. The number of activated voxels is matched (equivalent to $t > 4.3$), and contiguity >3 for viewing.

RESULTS AND DISCUSSION

Motor-related clusters were identified for both the task and resting state cluster maps. Results for a typical subject during the motor task are shown in Figure 1. The bilateral activation is seen in both the results from the model-free online algorithm and the standard correlation map formed in post-processing, and is seen in the online results even after one trial. Figure 2 shows the functional connectivity results using the model-free online algorithm and the offline seed-based approach. Significant correlation between the contralateral and ipsilateral motor cortices are evident, as well as the supplementary motor area. The functional connectivity pattern can be assessed during the scan with the online algorithm, and does not require an additional scan or user-biased seed ROI.

Thus, the dynamic clustering algorithm can detect functional connectivity in both task and resting-state fMRI. This allows for real-time model-free assessment of functional connectivity in both task and resting state fMRI, extending its applicability for clinical use. Possible applications include the online monitoring of patient state in pathological (e.g. epilepsy) or single-change states (e.g. pharmacological studies), as well as the further elucidation of the dynamics of functional connectivity.

REFERENCES

[1]Cox, RW, et al. 1995. MRM 33:230
[2] Gembris, et al. 2000 MRM 43:259
[3] Biswal B,et al. 1995. MRM 34:537
[4] Peltier SJ, Noll DC. 2002. Neuroimage, 16:985
[5] Lowe MJ,et al. 2002. Radiol 224(1):184
[6]Li SJ, et al. 2000 MRM 43:45.
[7] Barth M, et al. Proc ISMRM 2003, 1817
[8]Lowe, M.J, et al. 1998. Neuroimage 7:119
[9] Cordes, D, et al. 2000. Am J Neuroradiol 21:1636

Acknowledgements: Supported by the Whitaker Foundation, Georgia Research Alliance, and NIH grants RO1EB002009, R01EB00321