Quantitative Measurement of Signal Fluctuations in ASL from Resting State Functional Networks

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Introduction: Spontaneous signal fluctuations in the resting brain have been studied widely using blood oxygenation level-dependent (BOLD) MRI[1]. Recently the arterial spin labeling (ASL) technique has shown the capability to detect the large-scale organized resting state networks, very similar to the resting state networks detected from BOLD[2]. Quantitative physiologic measurement of signal fluctuations from the resting state networks is an important and understudied area that may enable improved understanding of brain function. ASL perfusion measurement can provide a direct quantitative measure of signal fluctuations in physiologic units. Here, we quantify the signal fluctuations of resting state networks using the ASL technique.

Methods: Resting-state pulsed-continuous arterial spin labeling (PCASL)[3] data was acquired in 20 healthy volunteers (30.3 ± 4.6 years old) on a GE 3 Tesla scanner. Thirty-nine 3D images were collected for each volunteer. The imaging protocol and preliminary results in a small cohort were previously reported [2,4]. Seven common resting state networks were detected from our ASL data using MELODIC ICA[4].

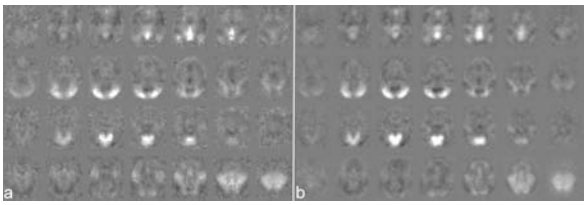

Fig. 1. Raw IC maps from (a) MELODIC and (b) infomax algorithm.

As is common for resting state analysis software, it is difficult to convert from the resting state independent components (ICs) to the corresponding perfusion signals within MELODIC. Instead, an open access ICA program using the *infomax* algorithm[5] was used to separate networks and perform the exact steps to convert the ICs back to the original perfusion signals. The grand mean perfusion of each smoothed and resampled 4D volume was scaled to the median mean perfusion of all 20 subjects. The scaled perfusion volume was demeaned by subtracting the mean signal over time at each voxel. The preprocessed ASL data were then input to the ICA program. This ICA algorithm was performed on the two-dimensional preprocessed data formed by temporal concatenation. The group ICA signal matrix S (size N×P, N=780, P= the total number of spatial points in each volume) can be decomposed as: S= M×C+ε, where M is a mixing matrix (size N×Q, Q=the number of ICs), C is the IC matrix (size Q×P), and ε is the residual noise.

Resting ASL signals fluctuate with two sources of signals: resting state ICs (M×C) and residual noise (ε). To compare the relative contribution of the resting state ICs and residual noise, signal fluctuation maps of the resting ICs and the residual noise were calculated. The fluctuation map of resting ICs was calculated as the standard deviation of the temporal signals from the signal model M×C. The residual noise was calculated by subtracting the ICs' signal model M×C from the demeaned ASL signal. To evaluate the effects of image smoothing on the two fluctuating sources, two different smoothing kernels of FWHM 6mm and 12mm were used to preprocess the ASL data before the infomax ICA analysis. The signal fluctuation map for each individual IC was also calculated as the standard deviation of the temporal signals from the IC. The relative signal fluctuation map was calculated relative to the mean perfusion map. The mean perfusion map was averaged over the time points and subjects.

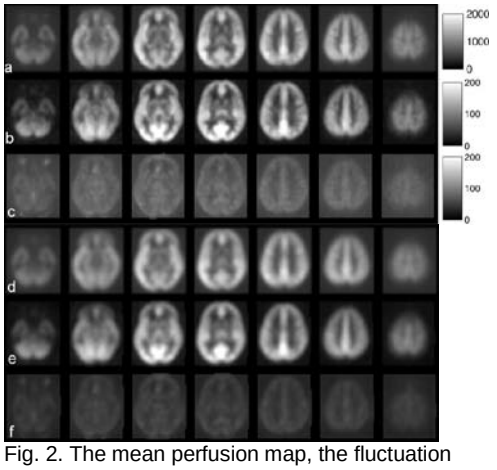

Fig. 2. The mean perfusion map, the fluctuation map of the ICs' signal model, and the fluctuation map of residual noise from the ASL data using a Gaussian kernel FWHM of (a-c) 6 mm and (d-f) 12 mm.

Results & Discussions: The ICs calculated from the infomax ICA algorithm were similar to those calculated from the MELODIC (Fig. 1). The ICs fluctuation map and residual noise fluctuation map are shown in Fig. 2. The ICs fluctuation map were approximately 10% of the gray matter perfusion (see the gray-level scales). The IC fluctuations were much larger than the residual noise fluctuations. With 12mm smoothing kernel, residual noise fluctuation were reduced (signal of gray matter: 49 vs. 82) but the IC fluctuations remained similar (signal of gray matter: 121 vs. 127). This indicates that the resting state structured noise in ASL data is large relative to the residual noise and it cannot be reduced with larger smoothing kernels. The fluctuation map for each individual IC is shown in Fig. 3. The ICs fluctuated up to 18% of the perfusion signal at a pixel-by-pixel level. Regional signal fluctuation amplitude varies between the different networks (Table 1). The lateral and medial visual networks showed the largest regional relative fluctuations.

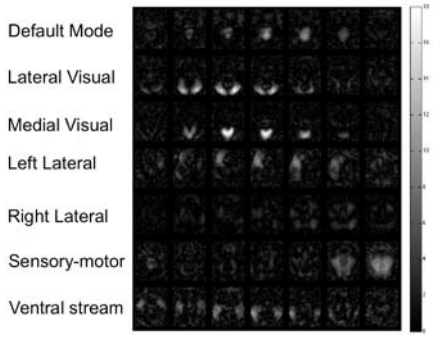

Fig.3. The relative signal fluctuation maps of the individual ICs to the mean perfusion.

Conclusions: 3D ASL perfusion data can provide a quantitative measurement of signal fluctuations within the resting state networks. This capability may be used to further study the physiology of the fluctuations and for improved noise reduction and statistical analysis of future ASL studies.

References: 1. Raichle et al, Proc. Natl. Acad. Sci. 2001;98:676-82. 2. Liang et al, Int J Imaging Syst Technol 2012;22:37-43. 3. Dai et al, Magn Reson Med 2008;60(6):1488-97. 4. Dai et al, ISMRM 2012 #2018. 5. A. Bell and T. Sejnowski, Neural Computation, 1995;7:1129-59.

Table 1. Regional relative fluctuation of resting state networks

Relative fluctuation	Default mode	Lateral visual	Medial visual	Left lateral	Right lateral	Sensory motor	Ventral stream
	7.68%	10.58%	11.15%	8.08%	3.55%	7.45%	6.64%