FILTERING FMRI USING A SOCK

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Introduction: It is well known that blood oxygenation level dependent (BOLD) function magnetic resonance imaging (fMRI) is restricted by low signal to noise and various artifacts. Sources of these artifacts vary from motion to physiological noise. Independent components analysis (ICA) is a data-driven analysis approach that is increasingly being used to filter fMRI of such noise [1-3]. However, one of the problems with ICA remains the interpretation of the results. Recently, we developed an automatic classifier that we call a Spatially Organised Component Klassifikator (SOCK) [4], which uses spatial criteria to help distinguish plausible biological phenomena from likely instrument and physiological noise. SOCK was shown to successfully remove artifactual components, without rejecting biological components in resting state data. Here, we utilize SOCK to automatically filter a conventional fMRI block-design language study. We assess the performance of the filter by comparing the significance of activation obtained in a conventional general linear model (GLM) analysis of the data with and without the use of SOCK.

Methods: Functional MRI data of five healthy controls (age range: 26-70, mean=48.30, 4 female) was acquired using a GE 3T Signa LX scanner with a standard EPI sequence. Each subject performed a standard language fMRI study. This behavioural paradigm involved four 30-second blocks of task alternating with blocks of rest (visually presented cross hair). During task blocks subjects performed covert orthographically-cued lexical retrieval (OLR) – a verbal fluency task where the subject was required to generate words beginning with each of a series of displayed letters. Statistical analysis using the GLM was performed in SPM8 [5]. Two analyses were performed – one on data filtered by ICA+SOCK, and the other on unfiltered data. ICA was performed using the MELODIC tool in FSL software [6]. The SOCK filter classified ICs into categories of definite artifact, possible artifact and unlikely artifact. A denoised time series omitting only the definite artifact ICs was created. To assess the effectiveness of SOCK, we define a ratio of the sum of t-statistics pre/post-SOCK for all voxels in a pre-defined region of interest (ROI) of the language area. This ROI consisted of left lateral language regions [7].

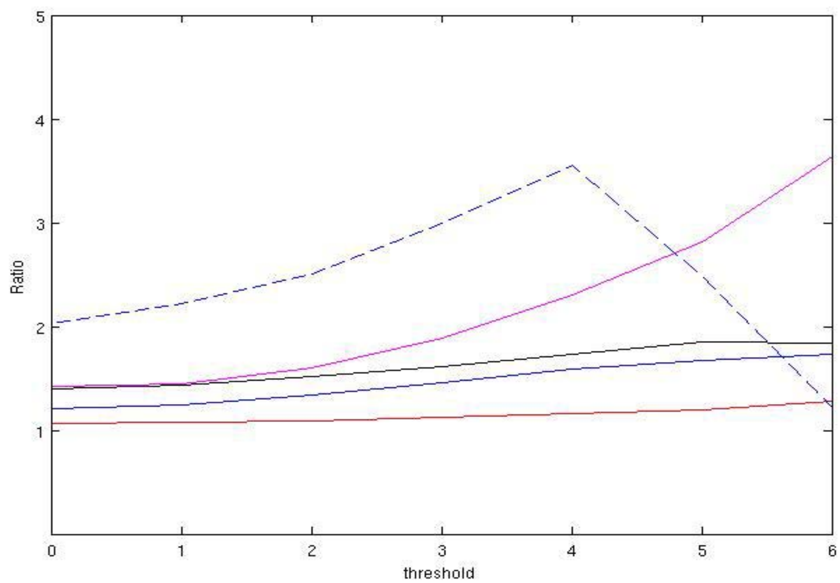

Fig. 1: Ratio of the sum of t-statistics for all voxels within our ROI vs threshold for five subjects. All curves yield ratio's above one, demonstrating the effectiveness of SOCK.

Results: A summary of the results is provided in figure 1, showing a plot of the Ratio of the sum of t-statistics for all voxels (pre/post SOCK) within our ROI vs threshold for five subjects. As expected, all ratios are above one, indicating, that the significance of the activation in the language region has improved. Figure 2 provides a qualitative visualisation of improved performance. All the subjects yielded increased activation within the language ROI.

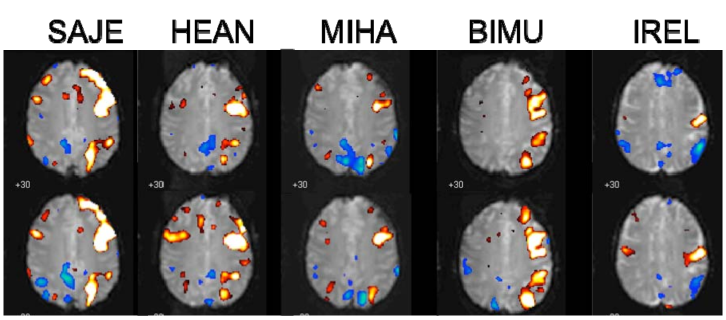

Fig. 2: Top Row: Pre-SOCK. Bottom Row: Post-SOCK. A sample slice from the SPM analysis pre and post SOCK for five subjects (thresholded at 3.1). Activation (overlaid onto a normalized template) in red/blue indicates positive/negative BOLD responses respectively. All subjects showed improvements in t-statistics after filtering with SOCK.

Conclusions: These preliminary results demonstrate the SOCK algorithm can be successfully used in filtering fMRI. The use of the SOCK algorithm to filter fMRI substantially increased the significance and extent of activation in all subjects in this fMRI language study.

References: 1. Perlbarg et al., *Magnetic Resonance Imaging,* 2007*, 25*, 35-46. 2. Sui et al., *NeuroImage,* 2009*, 46(1)*, 73-86. 3. Tohka et al., *NeuroImage,* **2008***, 39*, 1227-1245. 4. Bhaganagarapu et al., *NeuroImage,* **2009***, 47(S1)*, S39-S41. 5. http://www.fil.ion.ucl.ac.uk/spm/software/spm8/ 6. Smith et al., *NeuroImage*, **2004,** 23(S1):208-219. 7. Sveller et al., *Neurology,* **2006***, 67(10)*, 1813-1817.