Automatic detection of spatiotemporal propagating patterns in BOLD fMRI of the rats using an ICA based approach

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Target Audience: Functional MRI (fMRI) and signal/image processing communities.

Background and purpose: Low frequency fluctuations (LFFs) in resting state fMRI have been used to map functional connectivity (FC) in humans as well as animal models [1, 2, 3]. Previous work has reported the presence of automatically detectable spatiotemporal patterns in LFFs in humans as well as rats [3, 4]. The iterative automatic detection method proposed by Majeed et al. (referred to as iterative pattern-finding method, or IPFM henceforth for brevity) relies on manual delineation of an ROI for detection of each pattern and requires repetition of the process with random initializations [4]. In this article, we present an independent component analysis (ICA) based approach for detection of propagating spatiotemporal patterns in LFFs. This approach allows detection of multiple propagation patterns using a one-pass analysis, without the need for ROI specification and repetition with random initial conditions.

Methods: *Animal Imaging:* Imaging was performed on 9.4T Bruker scanner. The rats (n = 8) were sedated using medetomidine. For each rat, a series of gradient echo EPI images was acquired of 4-5 coronal slices (covering somatosensory and visual cortices, caudate-putamen (CP) and parietal association area (PrA)) with TR = 500 ms, TE = 20 ms, matrix size = 64x64, in-plane resolution = 300-400 microns and 1200 repetitions. *Preprocessing* included spatial blurring, temporal filtering (0.08-0.2 Hz), and normalizing of each time series to unit variance. *Spatiotemporal pattern detection using ICA:* The preprocessed data were divided into temporally overlapping spatiotemporal segments (segment length: 10s; overlap: 75%). The segments (after removing non-brain regions) were vectorized, and ICA (using fastICA) was performed using these spatiotemporal vectors as the mixture observations (after reducing the model order to 20 using principal component analysis). Similar approach (involving ICA with segments of the data treated as observations) has been previously used to detect independent sources from single-channel data and to learn patterns that are well matched to the data [5,6]. We will refer to this approach as ICA on overlapping segments (or ICA_{OS}) henceforth. The resultant spatiotemporal independent components were reshaped appropriately, converted to z-score, thresholded ($|z| > 2$) and overlaid on anatomical images.

Results: 20 spatiotemporal patterns were obtained for each rat. Many of these patterns were delayed versions of a single pattern, and only one of them was chosen for further comparison. Fig 1 shows frames from the three patterns that were reproducibly detected across all the rats. Pattern 1 consists of traveling wave of activity propagating in lateral to medial direction (spanning somatosensory cortex, PrA and visual cortex). Pattern 2 consists of bilateral activity in CP. Patterns 1 and 2 have been detected in previous works using visual inspection and IPFM [3,4]. Correlation between the patterns obtained using ICA_{OS} and IPFM (at the optimal lag) was 0.74±0.08 for Pattern 1 and 0.67±0.20 for Pattern 2 when computed using voxels belonging to the whole brain mask (0.84±0.08 and 0.86±0.22 respectively, when computed using voxels belonging to the respective ROIs). This confirms the ability of our approach (ICA_{OS}) to detect the patterns that have been reported previously. Pattern 3 shows bilaterally synchronous propagating activity in secondary somatosensory cortex (SII). This pattern may not be detected using IPFM when the ROIs are placed in cortex or CP [4]. However, when the ROI is placed in SII, the same pattern can be detected using IPFM (Fig 2, correlation with ICA_{os}-derived Pattern 3 = 0.82±0.09). This suggests that the approach proposed in this article (ICA_{OS}) can detect the patterns which may only be detected after delineation of a particular ROI when IPFM is used.

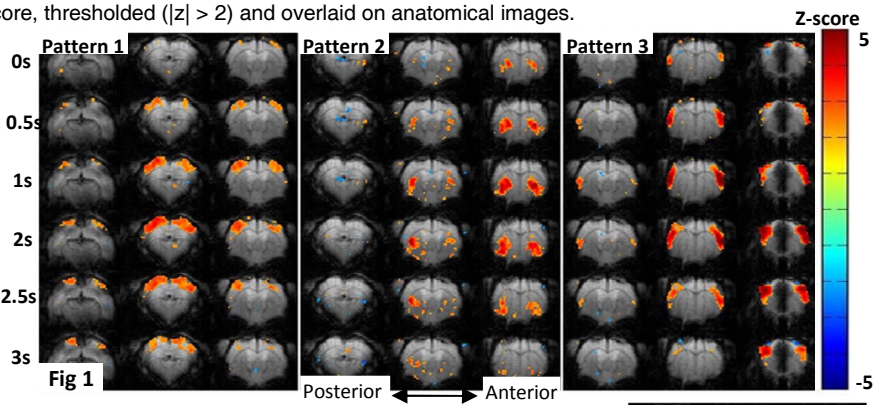

Fig 1

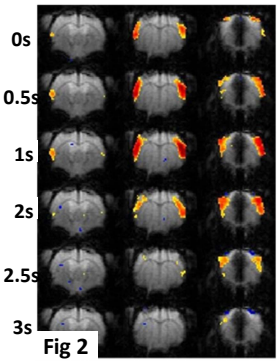

Fig 2

Discussion and Conclusions: Our results demonstrate that ICA_{OS} provides a data driven method for detection of spatiotemporal patterns of spontaneous activity in the brain. Unlike IPFM [4] - the only method available to date for detection of spatiotemporal patterns in LFFs, this method does not rely on user-defined ROIs and can detect multiple patterns in a one-pass analysis. This method was able to detect not only the previously reported patterns in rat data, but also a new pattern that may also be detected by IPFM with a manually specified ROI in SII. In conclusion, ICA_{OS} may provide a more efficient alternative for detection of spatiotemporal patterns in LFFs. As stated above, this method detects multiple temporally shifted versions of each pattern. Clustering can be used to group the shifted versions of the same pattern. Future work will involve 1) assessment of sensitivity of ICA_{OS} on the analysis parameters such as window-length, overlap and temporal filtering, and 2) application ICA_{OS} on data obtained from subjects with different physiological and pathological conditions to extract latent patterns that differentiate between different conditions.

References:

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