Identifying brain networks using tensor decomposition of multiple subject asynchronous task fMRI

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Introduction

Correlation-based Functional connectivity (FC) can identify coherent brain activity across distributed and reproducible brain networks[1]. Dynamic FC identifies evolving changes in FC in response to intrinsic (e.g., network interactions) or extrinsic (e.g., task-related) factors. The most commonly used approaches for decoding dynamic FC are the sliding-window-based and ICA-based methods[2]. However, the former tends to over-smooth temporal dynamics and the latter requires either spatial or temporal independence, which may not be realistic as brain networks can overlap and be correlated in both space and time[3]. Recently, we developed a scalable and robust tensor-based sequential canonical polyadic decomposition (SRSCPD) framework[4] for dynamic FC identification in EEG that avoids these limitations. Here we combine this approach with the BrainSync[5] algorithm, which uses a time-domain orthogonal transform to synchronize resting and asynchronous task fMRI across subjects. We then use SRSCPD to identify common networks, and their associated dynamics, across subjects by computing a group tensor decomposition from asynchronously acquired task fMRI data.

Methods

We used motor task fMRI (tfMRI) data for 40 healthy subjects from the Human Connectome Project (HCP)[6], with two sessions per subject with opposite phase encoding directions, resulting in $\mathrm{S} = 80$ tfMRI sessions. Subjects were presented with visual cues to tap fingers, squeeze toes, or move their tongue[7]. Each block of movement lasts 12 seconds and is preceded by a 3-second cue. Timing varies across subjects and sessions. The tfMRI data were downsampled onto a $\mathrm{V} \approx 11\mathrm{K}$ surface tessellation where each vertex has a time series with $\mathrm{T} = 284$ samples. Using BrainSync, we synchronized time series from all other 79 sessions to the first session and stacked them together to form a tensor cube of size $\mathcal{X} \in \mathbb{R}^{\mathrm{V}\times\mathrm{T}\times\mathrm{S}}$. Finally, we performed SRSCPD[4] on $\mathcal{X}$ to compute a tensor decomposition with a maximum desired rank of $\mathrm{R} = 5$ and a non-negativity constraint only on the session mode.

Results

Fig. 1 shows all 5 components obtained from SRSCPD in (a) – (e). The first 3 columns show the spatial, temporal (overlaid with the task design blocks for the reference subject) and subject/session mode for each component, respectively. The last column shows the Welch power spectral density (PSD) of the temporal mode.

- For all 5 components, the subject/session modes are roughly uniform across all sessions, indicating approximately equal participation from all subjects.
- The temporal dynamics of both component (a) and (c) show clear peaks at the beginning of each task block, which is well aligned with the (delayed) cues. Spatially, (a) shows a clear fronto-parietal

attentional control network[8] and (c) shows a clear response in visual areas, which reflects the subjects' responses to the cues.

- Component (b) corresponds to the default mode network (DMN) which is also a task-negative network[9]. Indeed, a strong negative correlation with the cues can be directly observed from the temporal mode.
- Component (d) has a relatively fast (~0.3 Hz in PSD), global (spatial mode) and non-task-related (temporal mode) activity, suggesting that it may represent a residual respiration component common across all subjects.
- Component (e) reveals a clear tongue response. Corresponding networks for foot and mouth were not found in this decomposition.

Conclusion

Using SRSCPD with BrainSync, we identified changes in dynamic FC across 5 networks, 4 task-related and one corresponding to physiological noise in tfMRI data. Critically, although these networks were identified without using any prior information with regard to task designs, our results not only replicated the task design, but also demonstrated expected differences in the onset/offset of the DMN, visual, fronto-parietal and motor (tongue) networks. Further work is needed to elucidate higher order models, including the hand and foot motor networks.

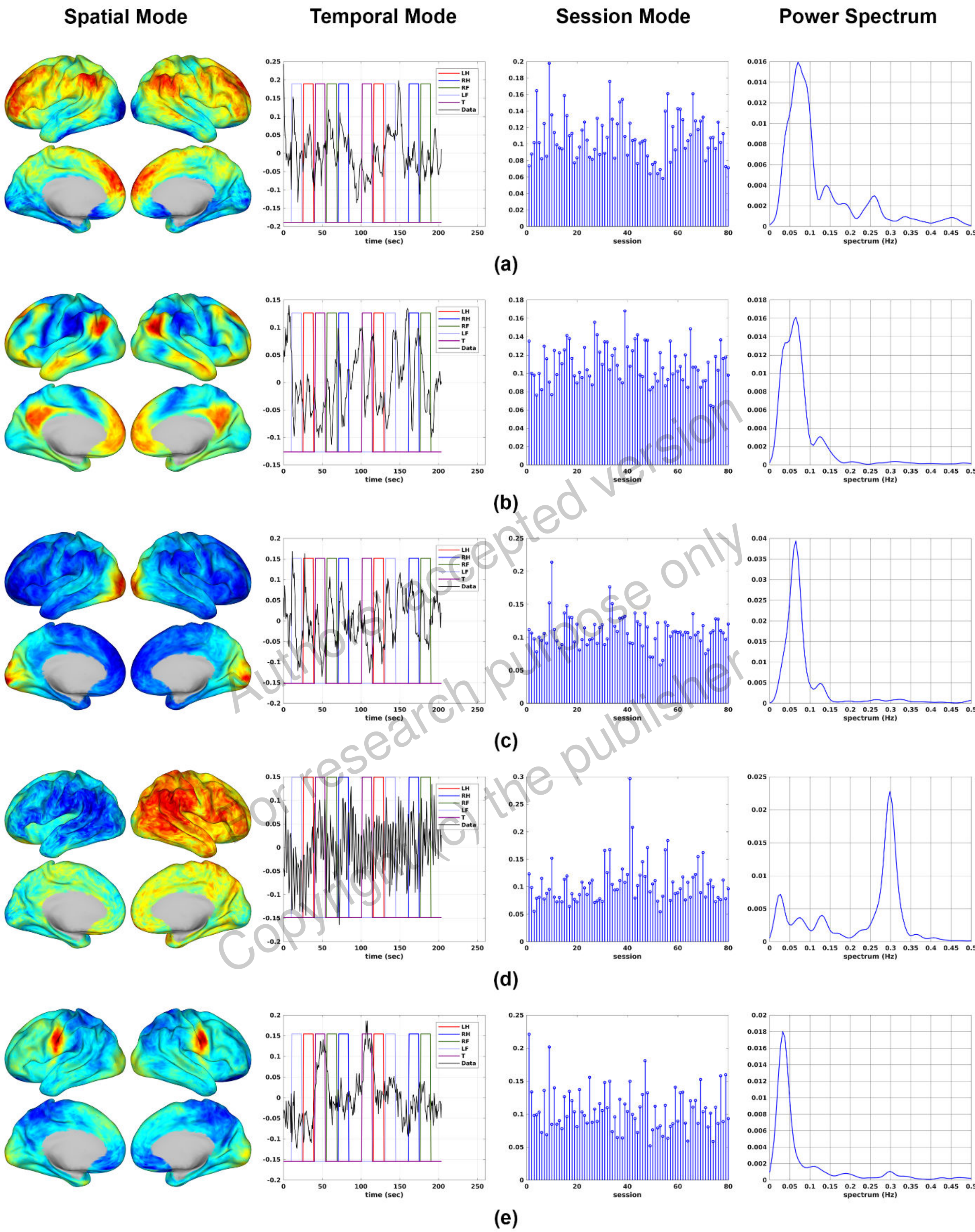

Figure 1: Five dynamic brain networks identified from synchronized task fMRI data using scalable and robust sequential canonical polyadic decomposition method. Columns from left to right: spatial mode, temporal mode, subject/session mode and the Welch power spectrum of the temporal mode. The temporal mode (with legend Data) is overlaid with the task design blocks of the reference subject (legend from top to bottom): LH: left hand; RH: right hand; RF: right foot; LF: left foot; T: tongue.

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