

Identifying Brain Networks Using Tensor Decomposition of Multiple Subject Asynchronous Task fMRI

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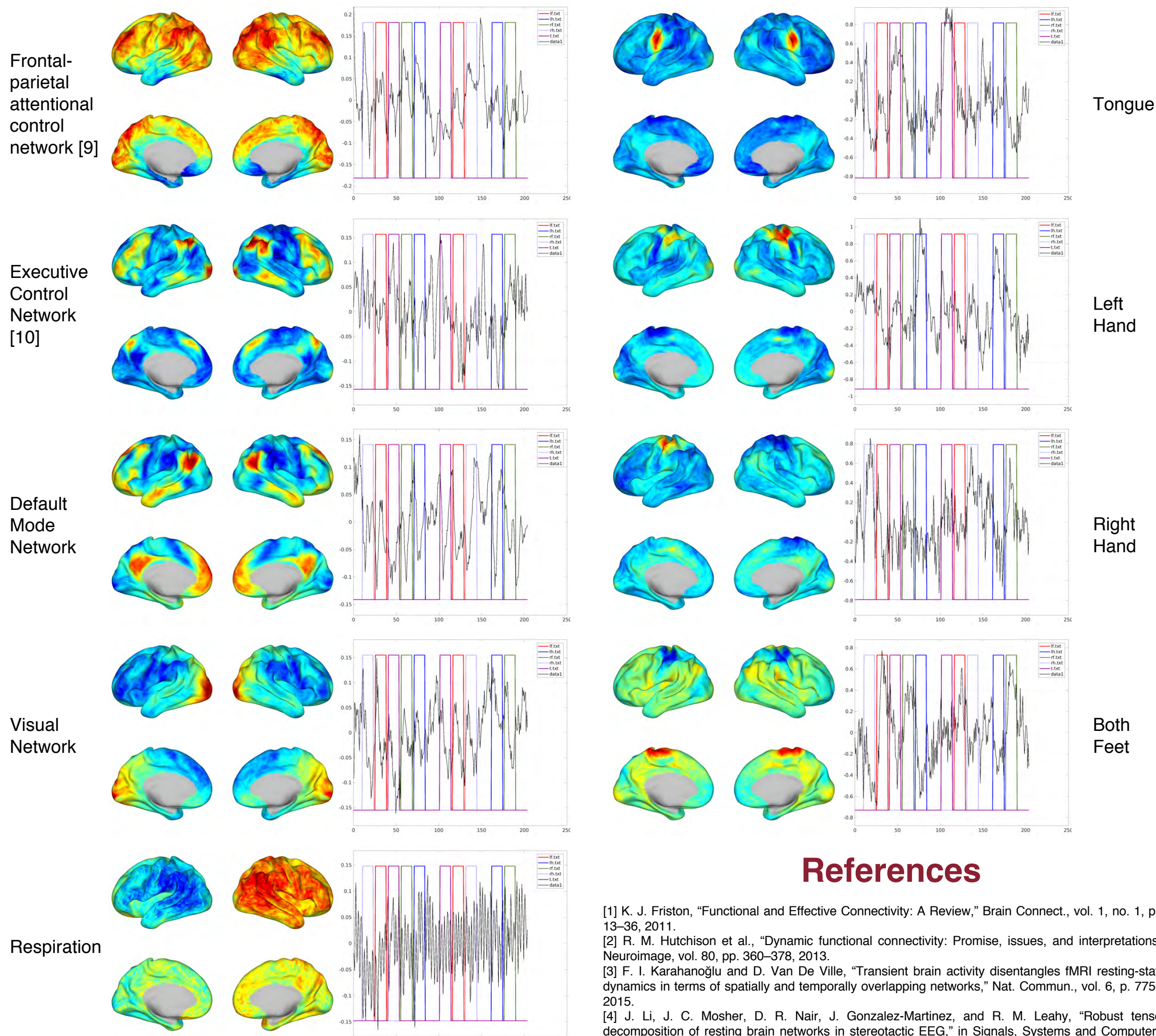
Introduction

- 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 (tfMRI) data.

Methods

- We used motor 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 $S = 80$ 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 $V \approx 11K$ surface tessellation where each vertex has a time series with $T = 284$ samples.
- Using BrainSync [5], we synchronized time series from all other 79 sessions to the first session and stacked them together to form a tensor cube of size $\mathcal{X} \in \mathbb{R}^{V \times T \times S}$.
- The rank of the tensor \mathcal{X} was reduced to 20 using a greedy CP decomposition [8].
- Finally, we performed SRSCPD [4] on rank-reduced tensor \mathcal{X} to compute a tensor decomposition with a non-negativity constraint only on the session mode.

Results



Discussion

- Using SRSCPD with BrainSync, we identified changes in dynamic FC across 9 networks, 8 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 networks.
- This framework can be extended to explore brain networks in more complicated task and resting state fMRI data.

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