

Brain network decomposition for naturalistic stimulus paradigm

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Introduction

Functional MRI acquired using naturalistic stimulus paradigms, such as movie-watching, incorporate dynamic and diverse sensory information. It has been shown to be more ecologically valid than traditional task-based fMRI and produce brain responses with higher stability than resting-state fMRI¹. Existing tools for analyzing this type of fMRI data often assume perfect temporal synchronizations between subjects, which, however, may not be valid due to differing responses and/or latency to the naturalistic stimuli in different subjects. Besides, popular methods such as inter-subject correlation, yield limited information about brain response patterns. Although commonly used independent component analysis² can discover more structures, it imposes independence constraint on either the spatial or temporal domain, which may not be physiologically realistic. To address these issues, we applied a combination of a temporal synchronization technique (BrainSync Alignment^{3,4}) and a tensor decomposition method (NASCAR⁵) to movie-watching data. The results showed that our method can provide rich information about the population’s common responses to the naturalistic stimuli, yet with a parsimonious model.

Methods

The minimally preprocessed 7T movie-watching fMRI data of 110 subjects from the Human Connectome Project were used^{6,7}. Each subject was recorded 4 fMRI sessions while watching audio-visual movies, which consist of film segments interleaved with rest periods. Each session ran ~15min (TR=1s). The fMRI data were resampled onto the cortical surface and co-registered to a common surface atlas. Each scan was represented as a $V \times T$ matrix ($V \approx 22K$ is the number of vertices across the two hemispheres, $T \approx 900$ is the number of time points). For each movie, we applied BrainSync Alignment (BSA) to jointly synchronize fMRI data across all subjects, Fig. 1a. For Movie 1, we formulated a tensor χ of size $V \times T \times S$ by concatenating the synchronized fMRI data along the 3rd dimension. NASCAR was then applied to approximate χ as a sum of 20 rank-1 tensors $\lambda_r \mathbf{a}_r \otimes \mathbf{b}_r \otimes \mathbf{c}_r$, each representing a distinct brain network which is composed of a spatial activation map (\mathbf{a}), a temporal dynamic (\mathbf{b}), and a subject participation level (\mathbf{c}). We also extracted 20 components using the spatial ICA (sICA) for comparison. We used the temporal mode of the auditory network (Fig 1b), from Movie 1 to predict soundtrack loudness of other movies by

transferring that auditory temporal response from G1 to each subjects' space in other sessions through G2 using a cascaded (invertible) BSA. The individual subjects' responses were then averaged together as the final prediction. Loudness measures, used as the "ground truth", were extracted using MIRtoolbox⁸ and convolved with a double gamma HRF. For sICA, we applied a pairwise BrainSync between two sessions of each subject to predict the responses, which were also averaged across all subjects.

Results

Fig. 1b shows the spatial maps of two networks identified using BSA+NASCAR and sICA. Both methods capture activations in auditory and visual cortex. Since the latter enforces spatial independences, spatial overlaps between the networks can be underestimated as shown in Fig. 1b. Fig 1c quantitatively confirms this observation by comparing the inter-network cross-correlation matrices between the two methods. Fig 2a shows the normalized sum of squared reconstruction error as a function of the number of identified networks. The errors are consistently lower using our method than that with sICA. Predictions of the loudness using the auditory temporal dynamics from BSA+NASCAR are also better correlated with loudness measures, for all 3 movies, Fig. 2b,c.

Conclusion

Our framework decomposes naturalistic fMRI data into brain networks under more physiologically valid assumptions, resulting in better stimulus neural encoding-decoding and better fit to the data than ICA.

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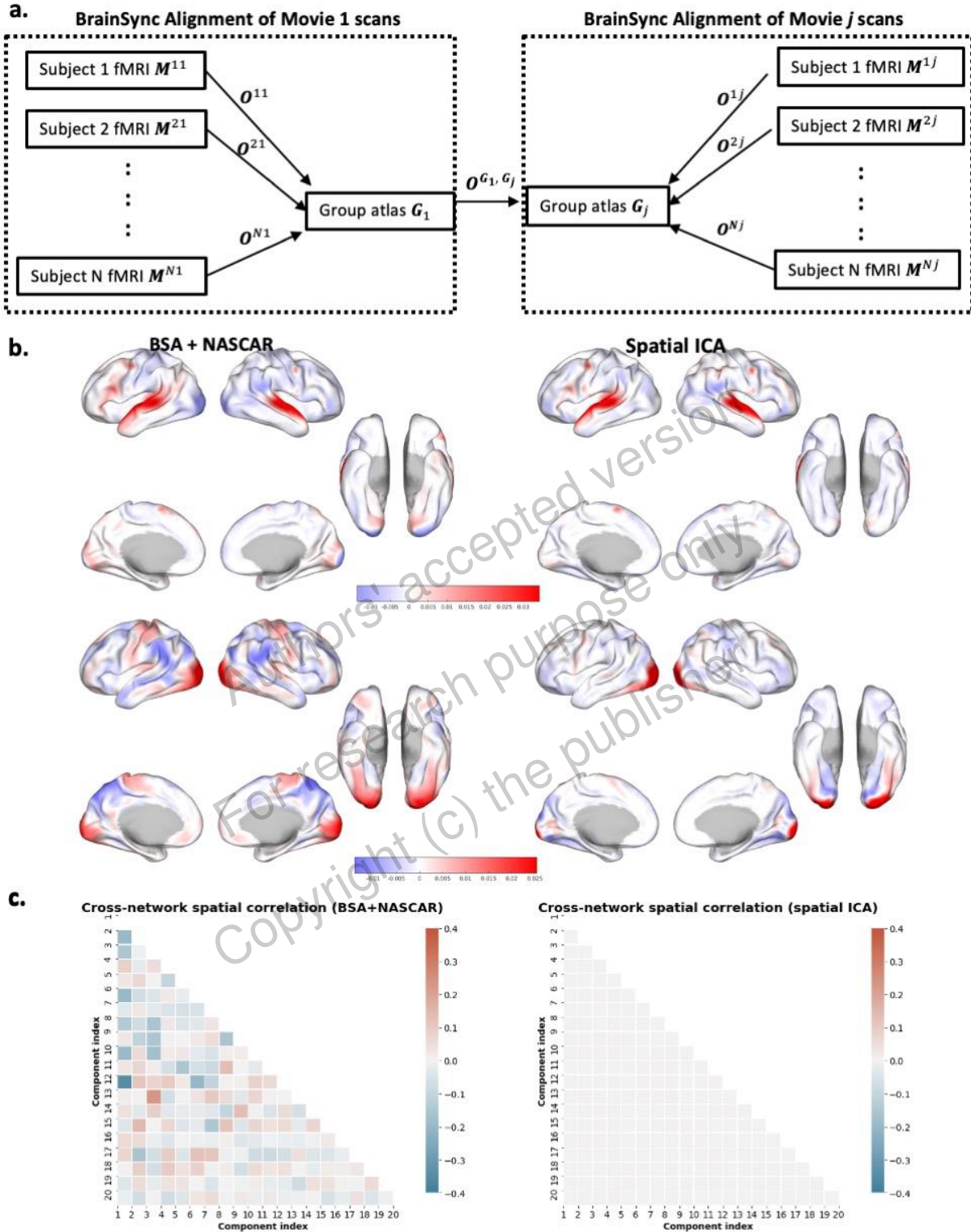


Figure 1 (a) Diagram of BrainSync Alignment (BSA) applied to the scans of two movies. For movie j , each subject i has a specific optimal transform O^{ij} which aligns the subject to the atlas. O^{G_1, G_j} is the orthogonal transform from G_1 to G_j with BrainSync (b) Decomposed spatial maps containing activations in auditory cortex (row 1) and visual cortex (row 2) using BSA+NASCAR and spatial ICA (c) Correlation matrices of spatial maps from BSA+NASCAR and spatial ICA

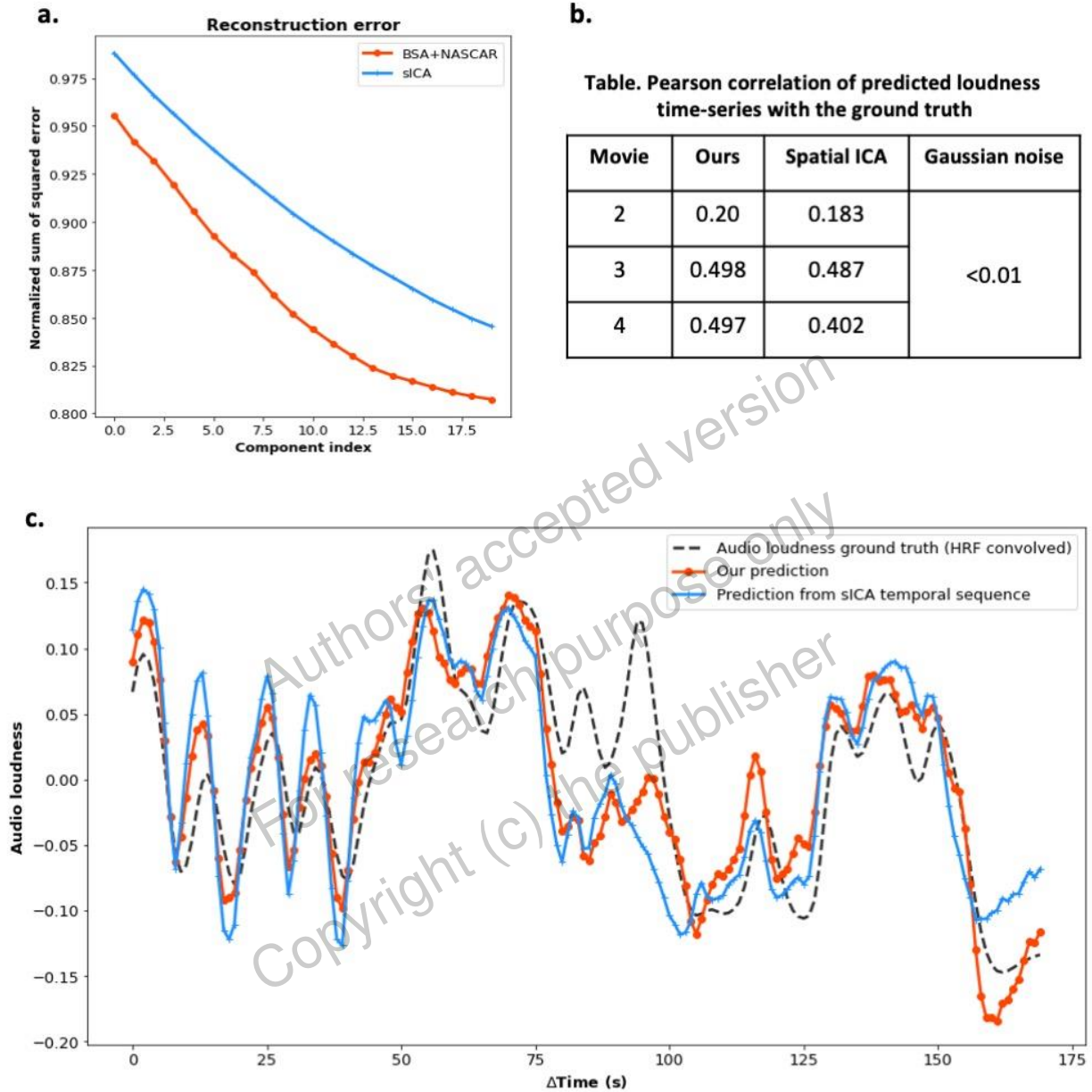


Figure 2 (a) Reconstruction errors using our method and spatial ICA (b) Pearson correlation of predicted loudness time-series with the ground truth using the temporal representations from our approach, sICA and Gaussian noise (c) Segments of ground truth audio loudness, our prediction, and prediction from sICA for Movie 4. Sequences are standardized for visualization purposes.

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