CONSTRAINED INDEPENDENT VECTOR ANALYSIS WITH REFERENCE FOR MULTI-SUBJECT FMRI ANALYSIS

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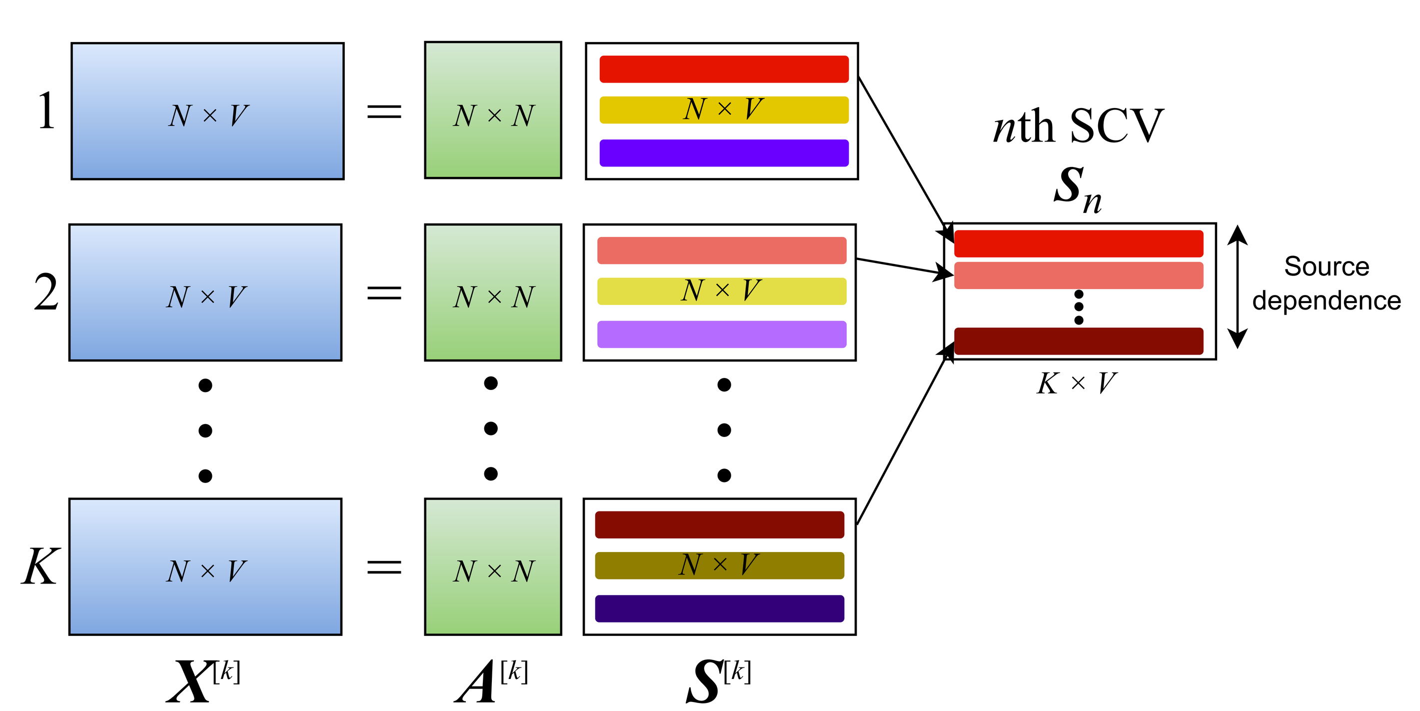
Introduction

- Independent vector analysis (IVA) is a joint blind source separation framework that exploits the **statistical dependencies across datasets**
- IVA has been successfully applied to various **neuroimaging** domains including multi-subject fMRI data analysis
- **Constrained IVA** (cIVA) is an effective way to bypass *computational issues of IVA* and improve the quality of separation by incorporating available **prior information**
- Existing cIVA algorithms often rely on **user-defined threshold** values to define the constraints

Contributions

- Propose an adaptive-reverse scheme to select variable thresholds in cIVA, named ar-cIVA
- Propose a threshold-free formulation of cIVA by leveraging the unique structure of IVA, named tf-cIVA
- Show the superior performance of the two proposed algorithms compared with existing cIVA algorithms in different settings
- Demonstrate that they provide meaningful and interpretable results from analyzing real fMRI data

Independent Vector Analysis (IVA)

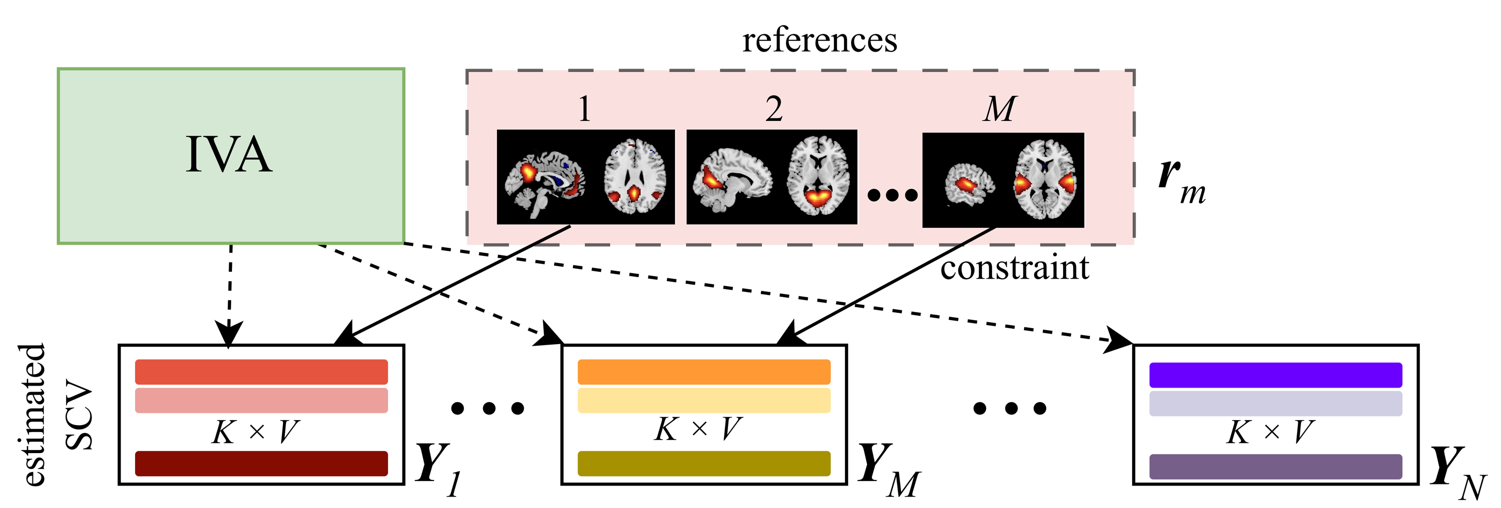


- The IVA cost function

$$\mathcal{J}_{\text{IVA}}(\boldsymbol{W}) \triangleq \sum_{n=1}^{N}\left(\sum_{k=1}^{K}\mathcal{H}(y_n^{[k]}) - \mathcal{I}(\boldsymbol{y}_n)\right) - \sum_{k=1}^{K}\log\left|\det(\boldsymbol{W}^{[k]})\right|$$

where $\mathcal{H}(y_n^{[k]})$ is the entropy of the nth estimated source for the kth dataset, $\mathcal{I}(\boldsymbol{y}_n)$ is the mutual information of the nth estimated source component vector (SCV), and $\boldsymbol{W}^{[k]}$ is the kth demixing matrix

Constrained IVA (cIVA)



- Constrained formulation of IVA with M references ($M \leq N$)

$$\min_{\boldsymbol{W}} \mathcal{J}_{\text{IVA}}(\boldsymbol{W}) \text{ s.t. } \epsilon(\boldsymbol{r}_m, \boldsymbol{y}_m^{[k]}) \geq \rho_m^{[k]} \quad \forall m = 1,\dots,M \text{ and } k = 1,\dots,K$$

Proposed Algorithms for Constrained IVA

Adaptive-Reverse Constrained IVA (ar-cIVA)

$$\min_{\boldsymbol{W}} \mathcal{J}_{\text{IVA}}(\boldsymbol{W}) + \frac{1}{2\gamma}\sum_{m,k}\left(\left(\max\left(0, \mu_m^{[k]} + \gamma\left(\rho_m^{[k]} - \epsilon(\boldsymbol{r}_m, \boldsymbol{y}_m^{[k]})\right)\right)\right)^2 - (\mu_m^{[k]})^2\right)$$

- **Augmented Lagrangian** method is used as a stable approach to constrained optimization
- **Adaptive-reverse scheme** alternates between two principles to select an appropriate threshold for each component
  - choosing the smallest value that does not satisfy the constraint

$$\rho_n^{[k]} = \text{argmin}\{\rho \in \mathcal{P} \mid \rho > \epsilon(\boldsymbol{r}_n, \boldsymbol{y}_n^{[k]})\}$$

  - choosing the largest value that satisfies the constraint

$$\rho_n^{[k]} = \text{argmax}\{\rho \in \mathcal{P} \mid \rho \leq \epsilon(\boldsymbol{r}_n, \boldsymbol{y}_n^{[k]})\}$$

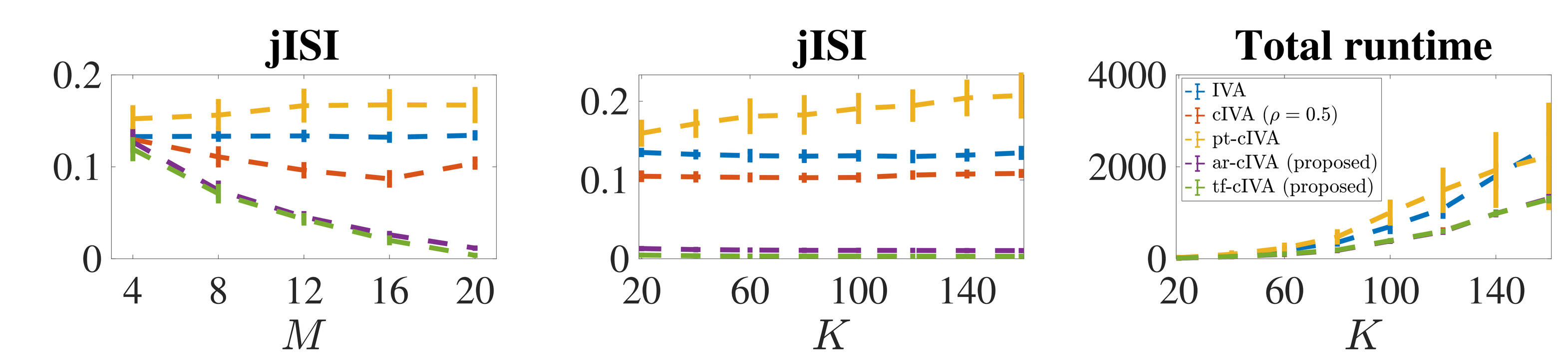
Threshold-Free Constrained IVA (tf-cIVA)

$$\min_{\boldsymbol{W}} \mathcal{J}_{\text{IVA}}(\boldsymbol{W}) + \frac{\lambda}{2}\sum_{m=1}^{M}\sum_{k=1}^{K}\left(\sum_{\substack{n=1\\ n\neq m}}^{M}\epsilon^2(\boldsymbol{r}_m, \boldsymbol{y}_n^{[k]}) - \epsilon^2(\boldsymbol{r}_m, \boldsymbol{y}_m^{[k]})\right)$$

- **Multi-objective optimization** adds a *regularization* cost to
  - **maximize** the similarity between the reference and the **corresponding** estimated source component
  - **maximize** the dissimilarity between the reference and all the **other** estimated source components
- Selecting an appropriate value for λ **balances the trade-off** between the IVA cost and the constraint-regularization cost

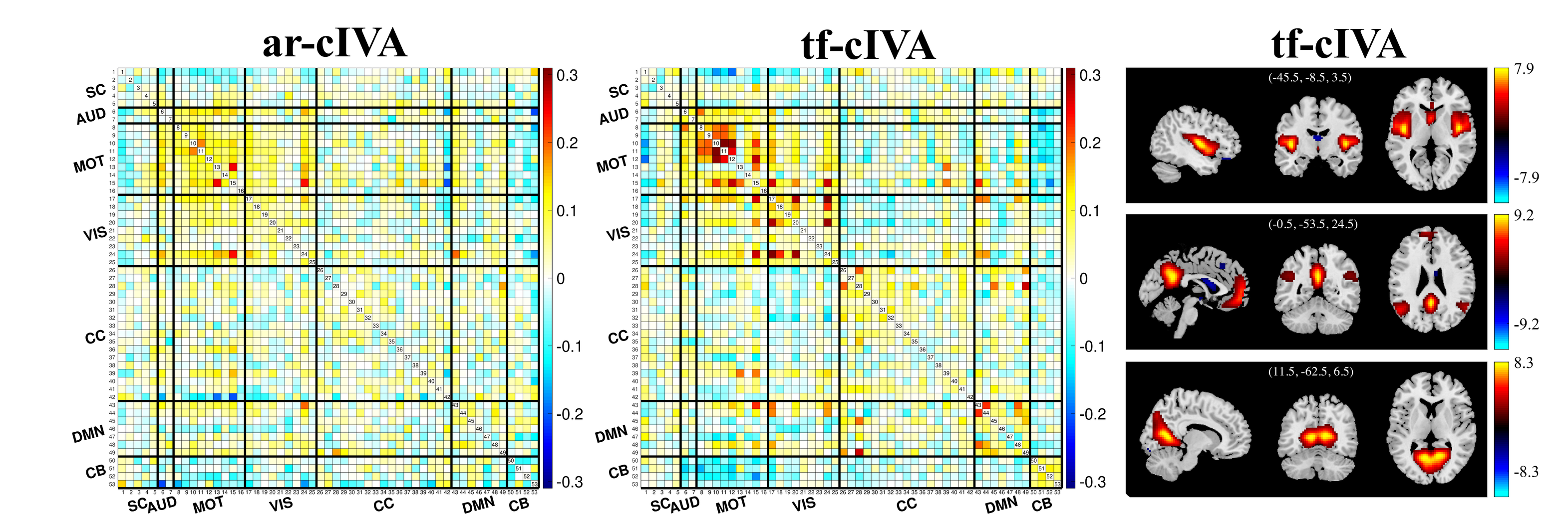
Experimental Results

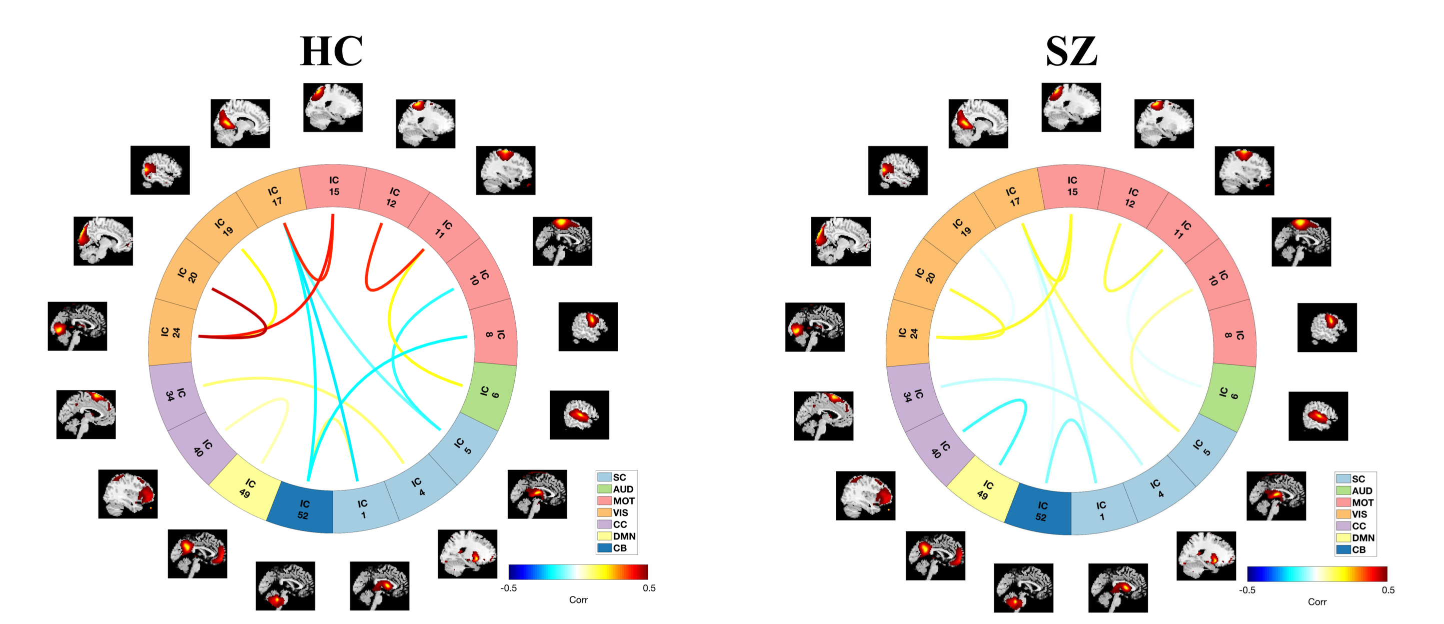
Hybrid simulation — Varying M and K



- Two proposed cIVA algorithms remarkably outperform (unconstrained) IVA and existing cIVA algorithms
- tf-cIVA slightly outperforms ar-cIVA

fMRI data analysis — $K = 98$ subjects





Summary

- tf-cIVA shows more meaningful and interpretable results when applied to real fMRI data
- tf-cIVA preserves subject variability and shows significant group differences between healthy control (HC) and schizophrenia patients (SZ)

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