A state-space model for inferring effective connectivity of latent neural dynamics from simultaneous EEG/fMRI

Tao Tu[1], John Paisley[2], Stefan Haufe[3], and Paul Sajda[1,2]

[1]Department of Biomedical Engineering, [2]Department of Electrical Engineering, Columbia University, New York, NY, USA

[3]Berlin Center for Advanced Neuroimaging, Charité-Universitätsmedizin Berlin, Germany

tt2531@columbia.edu

NeurIPS 2019

Abstract

Inferring effective connectivity between spatially segregated brain regions is important for understanding human brain dynamics in health and disease.

In this study, we develop a **linear state-space model** to infer the **effective connectivity** in a distributed brain network based on **simultaneously recorded EEG and fMRI** data. Our method first identifies task-dependent and subject-dependent regions of interest (ROI) based on the analysis of fMRI data. Directed influences between the latent neural states at these ROIs are then modeled as a multivariate autogressive (MVAR) process driven by various exogenous inputs. The latent neural dynamics give rise to the observed scalp EEG measurements via a biophysically informed linear EEG forward model.

We use a **mean-field variational Bayesian** approach to infer the posterior distribution of latent states and model parameters. The performance of the model was evaluated on two sets of simulations.

Our results emphasize the importance of obtaining accurate spatial localization of ROIs from fMRI. Finally, we applied the model to simultaneously recorded EEG-fMRI data from 10 subjects during a Face-Car-House visual categorization task and compared the change in connectivity induced by different stimulus categories.

Experiment and Data

We collected simultaneous EEG and fMRI data on 10 subjects performing a Face-Car-House visual categorization task. On each trial, an image of either a face, car, or house, was presented for 100 ms. Subjects reported their choice of the image category by response press. Images were degraded with 35% and 50% phase coherence. In total, 360 trials (120 trial for each category) were collected for each subject.

Model

Link between state variables $\mathbf{s}_t$ and EEG observations $\mathbf{y}_t$

ROI model

$$\mathbf{x}_t = \mathbf{G}\mathbf{s}_t + \boldsymbol{\epsilon}_t$$
$$\boldsymbol{\epsilon}_t \sim N(0, \mathbf{Q}_x)$$
$$x_1, x_2 \sim N(s_1, \sigma_1^2)$$
$$x_3, x_4 \sim N(s_2, \sigma_2^2)$$
$$x_5, x_6 \sim N(s_3, \sigma_3^2)$$
$$x_7, x_8 \sim N(0, \sigma_0^2)$$

$$\mathbf{G}$$

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \\ x_7 \\ x_8 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} s_1 \\ s_2 \\ s_3 \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \epsilon_1 \\ \epsilon_2 \\ \epsilon_2 \\ \epsilon_3 \\ \epsilon_3 \\ \epsilon_0 \\ \epsilon_0 \end{bmatrix}$$

Taken together, our linear state-space model can be expressed as:

$$\mathbf{s}_t|\mathbf{s}_{t-1} \sim \mathcal{N}(\mathbf{A}\mathbf{s}_{t-1} + \sum_{k=1}^{K} \mathbf{B}^k m_t^k \mathbf{s}_{t-1} + \mathbf{D}\mathbf{u}_t, \mathbf{Q}_s), \qquad \mathbf{y}_t|\mathbf{s}_t \sim \mathcal{N}(\mathbf{C}\mathbf{s}_t, \mathbf{R}) .$$

where $\mathbf{C} = \mathbf{L}\mathbf{G}$.

$\mathbf{s}_t$: latent state variables, ROI mean;

$\mathbf{y}_t$: EEG observations;

$\mathbf{x}_t$: EEG sources activity;

$\mathbf{L}$: lead-field matrix;

$\mathbf{A}$: intrinsic connectivity matrix;

m_t^k: k^{th} modulatory input at time t.

$\mathbf{B}^k$: k^{th} modulatory connectivity matrix;

$\mathbf{u}_t$: external input at each ROI;

$\mathbf{D}$: strength of $\mathbf{u}_t$;

$\mathbf{G}$: binary indicator matrix.

Inference

graphical model

$$\mathbf{R} = \mathbf{Q}_y + \mathbf{L}\mathbf{Q}_x\mathbf{L}'$$

variational Bayes (VB):

maximize the ELBO:

$$\mathcal{L}(q) = \int q(\mathbf{S}, \boldsymbol{\theta}) \log \frac{p(\mathbf{S}, \boldsymbol{\theta}, \mathbf{Y})}{q(\mathbf{S}, \boldsymbol{\theta})} d\boldsymbol{\theta} d\mathbf{S}$$

where $\mathbf{S} = \{\mathbf{s}_t\}_{t=1}^T$ and $\boldsymbol{\theta} = \{\mathbf{A}, \{\mathbf{B}_k\}_{k=1}^K, \mathbf{D}, \mathbf{Q}_s, \mathbf{R}\}$.

mean-field approximation:

VB-E Step: $\log q(\mathbf{S}|\mathbf{Y}) \propto \mathbb{E}_{\boldsymbol{\theta}}(\log p(\mathbf{S}, \boldsymbol{\theta}, \mathbf{Y}))$

VB-M Step: $\log q(\boldsymbol{\theta}|\mathbf{Y}) \propto \mathbb{E}_{\mathbf{S}}(\log p(\mathbf{S}, \boldsymbol{\theta}, \mathbf{Y}))$

VB-E Step (sequential update):

Kalman filtering:

$$q(\mathbf{s}_t|\mathbf{y}_1, \mathbf{y}_2, ..., \mathbf{y}_t) = N(\boldsymbol{\mu}_t^t, \boldsymbol{\Sigma}_t^t), \quad t = 1, 2, ...T$$

Kalman smoothing:

$$q(\mathbf{s}_t|\mathbf{y}_1, \mathbf{y}_2, ..., \mathbf{y}_T) = N(\boldsymbol{\mu}_t^T, \boldsymbol{\Sigma}_t^T), \quad t = 1, 2, ...T$$

VB-M Step (conjugate prior):

$$p(\boldsymbol{\eta}[r], \beta[r]|\boldsymbol{\alpha}) = \mathcal{N}\left(0, (\beta[r]\boldsymbol{\Lambda}_{\boldsymbol{\alpha}})^{-1}\right) \text{Gamma}(a_0, b_0),$$

$$p(\boldsymbol{\alpha}) = \prod_{i=1}^{(K+1)S+1} \text{Gamma}(c_0, d_0)$$

$$q(\boldsymbol{\eta}[r], \beta[r]|\mathbf{Y}) = \mathcal{N}(\bar{\boldsymbol{\mu}}[r], \beta^{-1}[r]\bar{\boldsymbol{\Sigma}}[r])\text{Gamma}(\bar{a}[r], \bar{b}[r])$$

$$q(\alpha_j|\mathbf{Y}) = \text{Gamma}(\alpha_j|\bar{c}_j, \bar{d}_j)$$

$$p(\mathbf{R}) = \text{InvWishart}(v_0, \mathbf{V}_0), \quad q(\mathbf{R}|\mathbf{y}) = \text{InvWishart}(v_n, \mathbf{V}_n)$$

Simulation

EEG only: inaccurate ROI localization

Real data

face-induced vs. house-induced connectivity pattern

additional connectivity required for house recognition

Conclusion

- **Accurate ROI localization provided by simultaneous EEG-fMRI significantly increases model performance.**
- **We propose a model-driven approach to infer the effective connectivity induced by multiple context-dependent inputs.**

Reference: Yang, Ying, et al. "A state-space model of cross-region dynamic connectivity in MEG/EEG." Advances in neural information processing systems. 2016.

Acknowledgement: this work was supported by the Army Research Laboratory (Cooperative Agreement W911NF-10-2- 0022) and the Army Research Office (Grant W911NF-16-1-0507).