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Adaptive identification of brain network dynamics



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I. Motivation

- Identification of brain network dynamics is of essential to
 - 1) uncover biomarkers for neurological disorders such as depression
 - 2) develop brain-machine-interfaces (BMIs) for adaptive closed-loop stimulation therapies of various neurological disorders



We have previously developed a framework to identify time-invariant linear state-space models (LSSMs) to describe spontaneous neural population dynamics, and input-output neural dynamics in response to electrical stimulation [1]

II. Methods

1. Dynamical brain network model

- Time-varying LSSM
- Focus on adaptive identification of spontaneous activity in this work

Hidden brain state Network IO dynamical model $= \mathbf{A}_t \mathbf{x}_t + \mathbf{w}_t$ $\mathbf{C}_t \mathbf{x}_t + \mathbf{v}_t$ \mathbf{V}_t

2. Adaptive identification method

- Propagator-based recursive subspace identification [2]
- Recursive estimation of the column space of the extended observability matrix $\Gamma_f = [\mathbf{C}^T, (\mathbf{C}\mathbf{A})^T, \dots (\mathbf{C}\mathbf{A}^{f-1})^T]^T$
- The recursive estimation is done through adaptively estimating the propagator via minimizing a quadratic cost function

 $\Gamma_f = \begin{bmatrix} \Gamma_{f_1} \\ \Gamma_{f_2} \end{bmatrix} = \begin{bmatrix} \Gamma_{f_1} \\ \mathbf{P}_f^T \Gamma_{f_1} \end{bmatrix} = \begin{bmatrix} \mathbf{I}_{n_x} \\ \mathbf{P}_f^T \end{bmatrix} \Gamma_{f_1} \qquad J_{IV}(\hat{\mathbf{P}}_f(t)) = \sum_{i=1}^{l} \beta^{t-i} \|\mathbf{z}_{f_2}(i)\xi_p^T(i) - (\hat{\mathbf{P}}_f(t)\mathbf{z}_{f_1}(i)\xi_p^T(i))\|^2.$

- However, brain network activity can have non-stationary and time-varying dynamics, especially when the patient's brain is monitored for a long time, e.g., using electrocorticography (ECoG)
- Consequently, we need to develop adaptive identification methods to track non-stationary dynamics in real time

References:

[1] Yang and Shanechi, Proc. IEEE EMBC, 2015 [2] G. Mercere, L. Bako, and S. Lecuche, Signal Processing, 2008

Can adaptively estimate an LSSM with a consist basis

3. Human ECoG data acquisition and processing

Electrocorticography (ECoG) data were collected from one patient for weeks. We took raw ECoG data from one electrode from cingulate (~ 168 hours)



- Test adaptive and previous non-adaptive LSSM identification method across 55 train-test pairs
- Performance measure: percentage of fit derived from one-step ahead prediction error on testing data

$$\textit{FIT} = 100\% \text{ indicates perfect fit} \quad fit_i = \left(1 - \frac{\|\hat{y}_{t|t-1}^{(i)} - y_t^{(i)}\|^2}{\|y_t^{(i)}\|^2}\right) \times 100\%, \ i = 1, 2, 3, 4, 5 \quad FIT = \frac{1}{5}\sum_{i=1}^5 fit_i$$

III. Results



Figure 1: Simulation results. (a) Identification of the column space of the extended observability

matrix of an example 3rd order constant-LSSM, with true in green, and estimation in black. (b)

Identification of a LSSM with step changing poles. (c) Identification of a LSSM with continuous

1. Simulations validate the adaptive estimation algorithm

- Can track various time-variations (Figure 1 (a) -(c))
- Have bias in estimation of fast poles (Figure 1 (d))



Test

Train with adaptive

Train with

non-adaptive

Power feature calculation

2. Adaptive estimation of brain network dynamics in human ECOG data



performance of adaptive estimation and non-adaptive estimation. Upper panel shows an example train-test set feature (out of 5). Lower panel shows the prediction performance on testing set. Here average model results from non-adaptive estimation

IV. Conclusions

- The adaptive identification algorithm can accurately identify non-stationary human ECoG dynamics
- The adaptive identification algorithm has bias in estimating poles that are close to zero. Refinement of the algorithm will be our future work

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