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Adaptive identification of brain network dynamics

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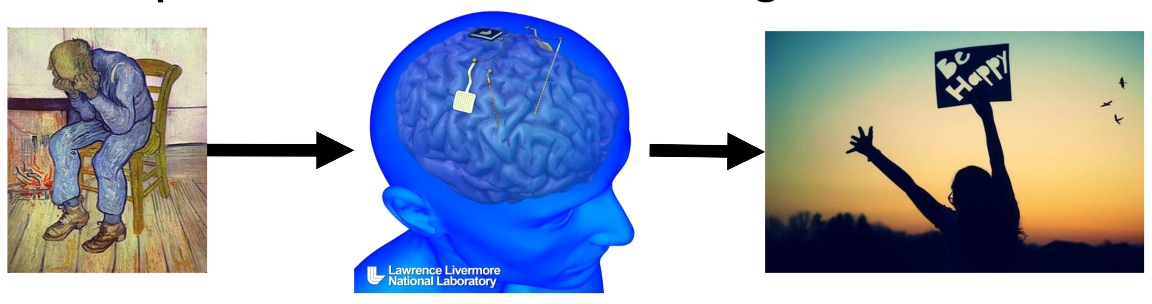
I. Motivation

- 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]
- 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:

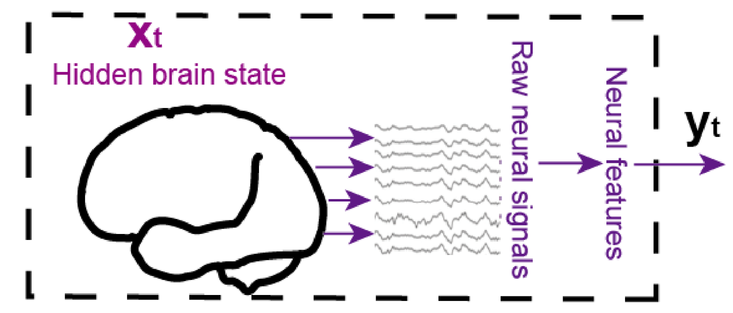
[1] Yang and Shanechi, Proc. IEEE EMBC, 2015

[2] G. Mercere, L. Bako, and S. Lecuche, Signal Processing, 2008

II. Methods

1. Dynamical brain network model

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



Network IO dynamical model

$$\begin{cases} \mathbf{x}_{t+1} = \mathbf{A}_t\mathbf{x}_t + \mathbf{w}_t \\ \mathbf{y}_t = \mathbf{C}_t\mathbf{x}_t + \mathbf{v}_t \end{cases}$$

2. Adaptive identification method

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

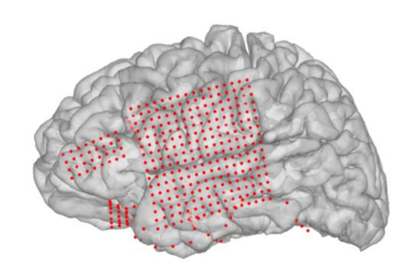
$$\mathbf{\Gamma}_f = \begin{bmatrix} \mathbf{\Gamma}_{f_1} \\ \mathbf{\Gamma}_{f_2} \end{bmatrix} = \begin{bmatrix} \mathbf{\Gamma}_{f_1} \\ \mathbf{P}_f^T\mathbf{\Gamma}_{f_1} \end{bmatrix} = \begin{bmatrix} \mathbf{I}_{n_x} \\ \mathbf{P}_f^T \end{bmatrix} \mathbf{\Gamma}_{f_1}$$

$$J_{IV}(\hat{\mathbf{P}}_f(t)) = \sum_{i=1}^{t} \beta^{t-i} \|\mathbf{z}_{f_2}(i)\xi_p^T(i) - (\hat{\mathbf{P}}_f(t)\mathbf{z}_{f_1}(i)\xi_p^T(i)\|^2.$$

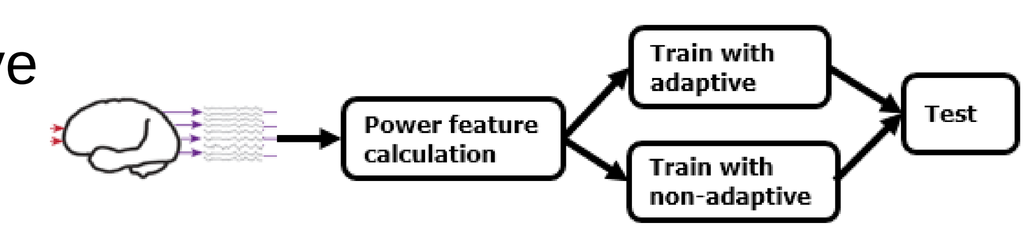
- Can adaptively estimate an LSSM with a consist basis

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)



- Powers within 5 frequency bands, i.e., [1 7]Hz, [8 12]Hz, [12 30]Hz, [30 100]Hz, and [100 200]Hz are extracted as features
- 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

FIT = 100% indicates perfect fit

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

III. Results

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))

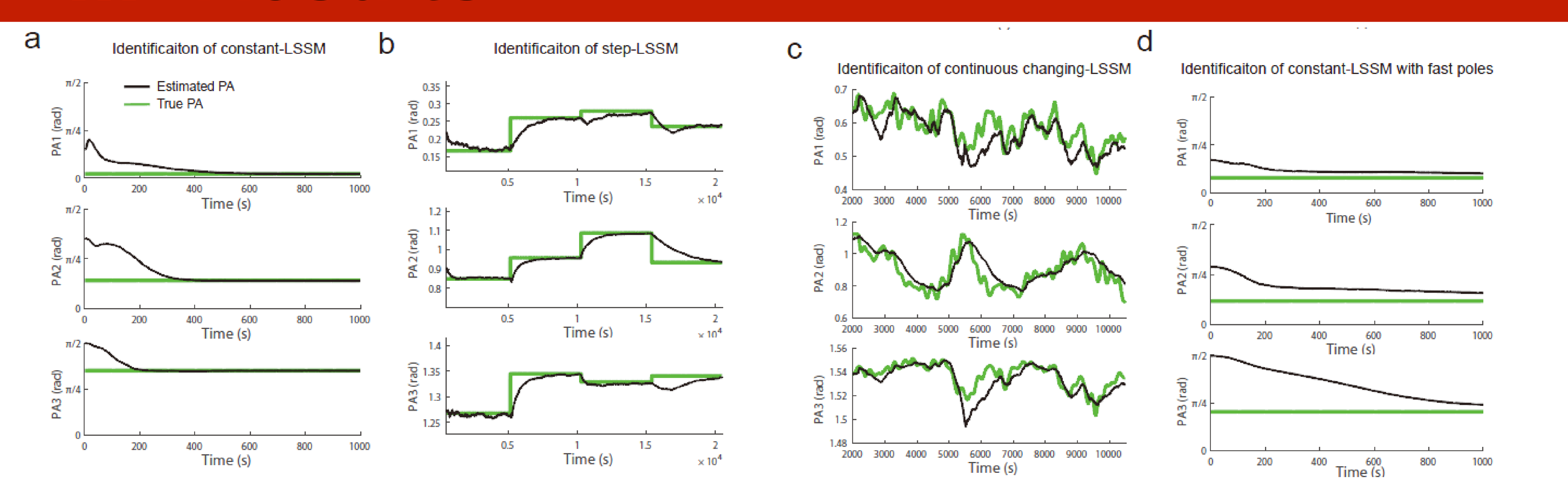


Figure 1: Simulation results. (a) Identification of the column space of the extended observability matrix of an example 3rd order constant-LSSM, with true in green, and estimation in black. (b) Identification of a LSSM with step changing poles. (c) Identification of a LSSM with continuous changing poles. (d) Identification of a constant-LSSM with fast poles.

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

- Adaptive estimation outperformed non-adaptive estimation (Figure 2 (a))
- Examples of adaptive and non-adaptive estimation (Figure 2 (b) – (d))

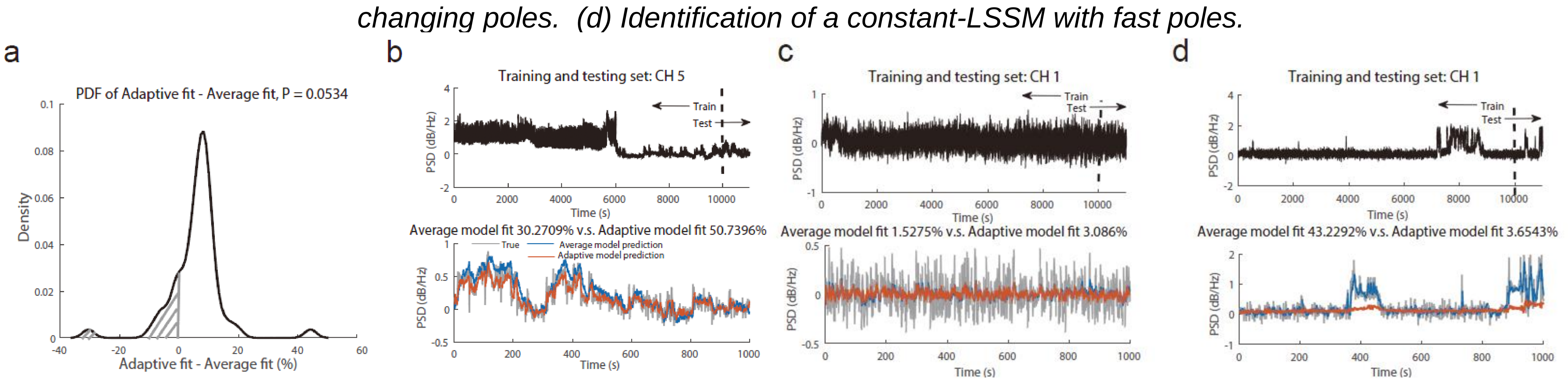


Figure 2: Human ECoG data analyses. (a) Distribution of adaptive FIT – non-adaptive FIT. (b-d) Examples of prediction performance of adaptive estimation and non-adaptive estimation. Upper panel shows an example train-test set feature (out of 5). Lower panel shows the prediction performance on testing 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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