State-Space Modeling of Brain Network Dynamics

*Omid G. Sani[1], Edward F. Chang[2], and Maryam M. Shanechi[1]
Dept. of Electrical Eng., Univ. of Southern California[1], Dept. of Neurological Surgery, Univ. of California, San Francisco[2]

Ming Hsieh Department of Electrical Engineering

USC Viterbi School of Engineering

I. Introduction

- Identification of brain network dynamics is important both for **understanding brain** function and for **designing closed-loop controllers** for control of brain states
- Linear state-space models (LSSM) are well suited for this purpose as:
  - They allow for modeling of the dynamics through a low-dimensional hidden state
  - They can easily be extended to include inputs (e.g. stimulation) into the system
  - They can be used to design well-established estimators (such as the Kalman filter) and controllers with performance guarantees (such as LQR and model predictive control)
- In this work we use an LSSM as follows to model the spontaneous brain activity:

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

  - $\boldsymbol{y}_t$: Neural features extracted from the neural signals
  - $\boldsymbol{x}_t$: An abstract hidden state representing the state of the brain

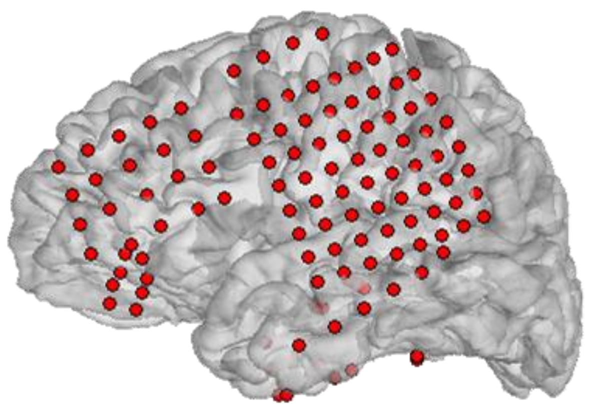
Reference

[1] P. Van Overschee and B. De Moor, Subspace Identification for Linear Systems. Boston, MA: Springer US, 1996.

II. Methods

1. Datasets

- Extraoperative electrocorticogram (ECoG) collected from 6 Epilepsy patients over periods of several days is used in this study (Chang Lab at UCSF).



sample electrode placement

2. Neural Features

- Features are extracted every 1 second
  From each channel, log-power of 5 frequency bands are extracted.
  Bands: $[1\ 8]Hz$, $[8\ 12]Hz$, $[12\ 30]Hz$, $[30\ 55]Hz$, and $[65\ 100]Hz$

3. System Identification

- LSSM system identification using Subspace Identification (SID) [1]
- System order is determined based on Akaike information criterion (AIC)

4. Performance Measure

- One step ahead prediction error is defined as:

$$\boldsymbol{e}_{t|t-1} = \boldsymbol{y}_t - C\hat{\boldsymbol{x}}_{t|t-1}$$

  - $\hat{\boldsymbol{x}}_{t|t-1}$: Kalman filter prediction of the hidden state
- Naïve predictor is a model-less predictor that predicts the next sample as the current one:

$$\hat{\boldsymbol{y}}_{t_{\text{Naïve}}} = \boldsymbol{y}_{t-1}$$

- Prediction performance for the ith feature is quantified using Normalized Root Mean Square Error:

$$\text{NRMSE}^{(i)} = \sqrt{\frac{\frac{1}{N}\sum_{k=1}^{N}\left(\hat{y}_k{}^{(i)} - y_k^{(i)}\right)^2}{var\left(y^{(i)}\right)}}$$

- One-sided paired t-test comparing LSSM and Naïve or mean prediction (better of the two for each feature) over the test set and across all features.

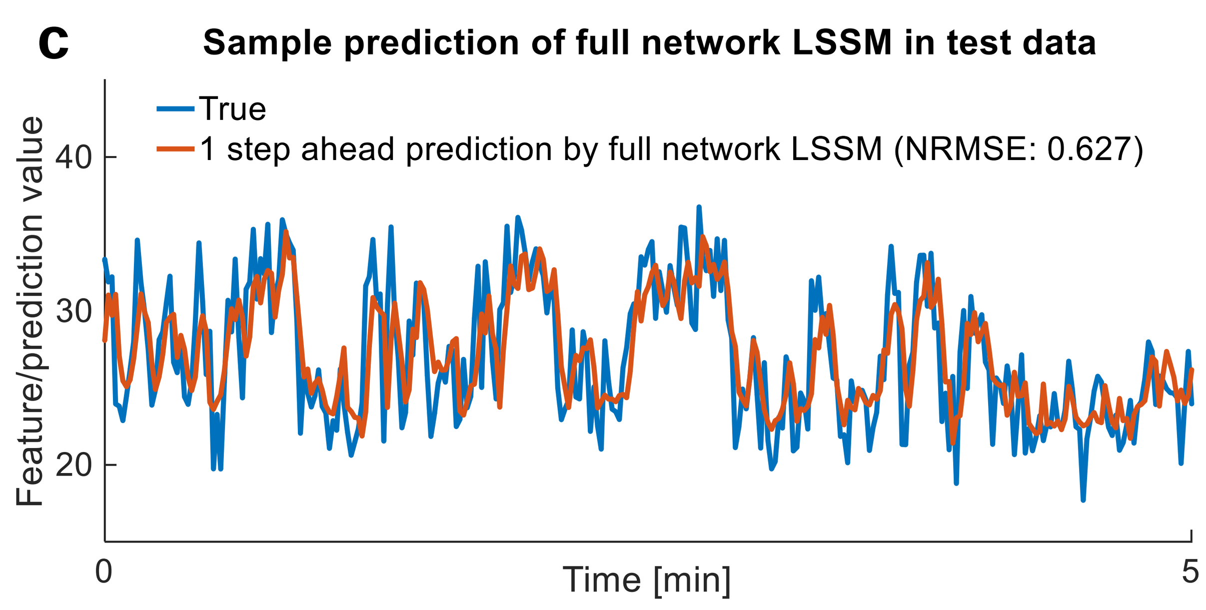
III. Results

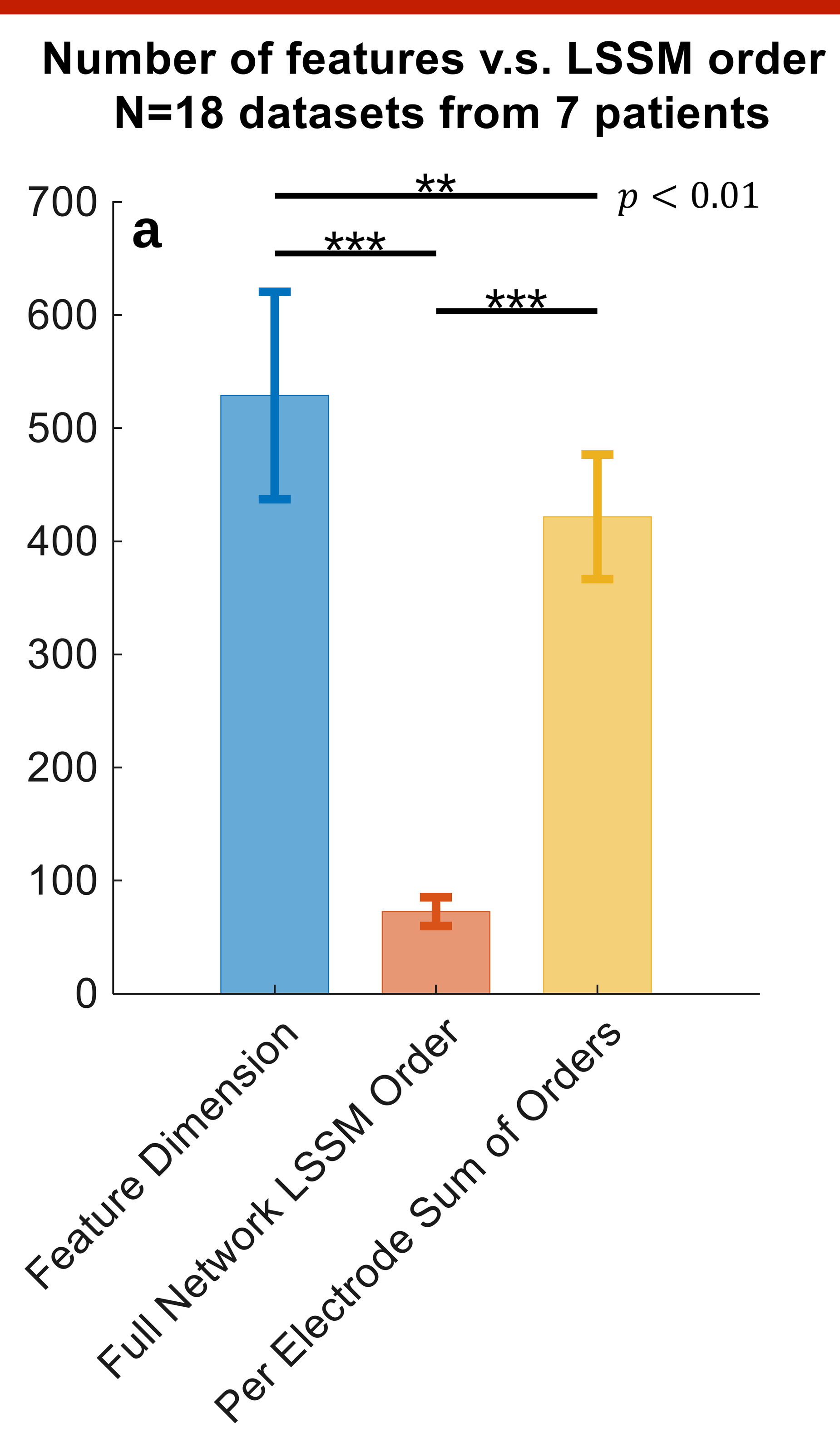
1. Identified LSSM Order

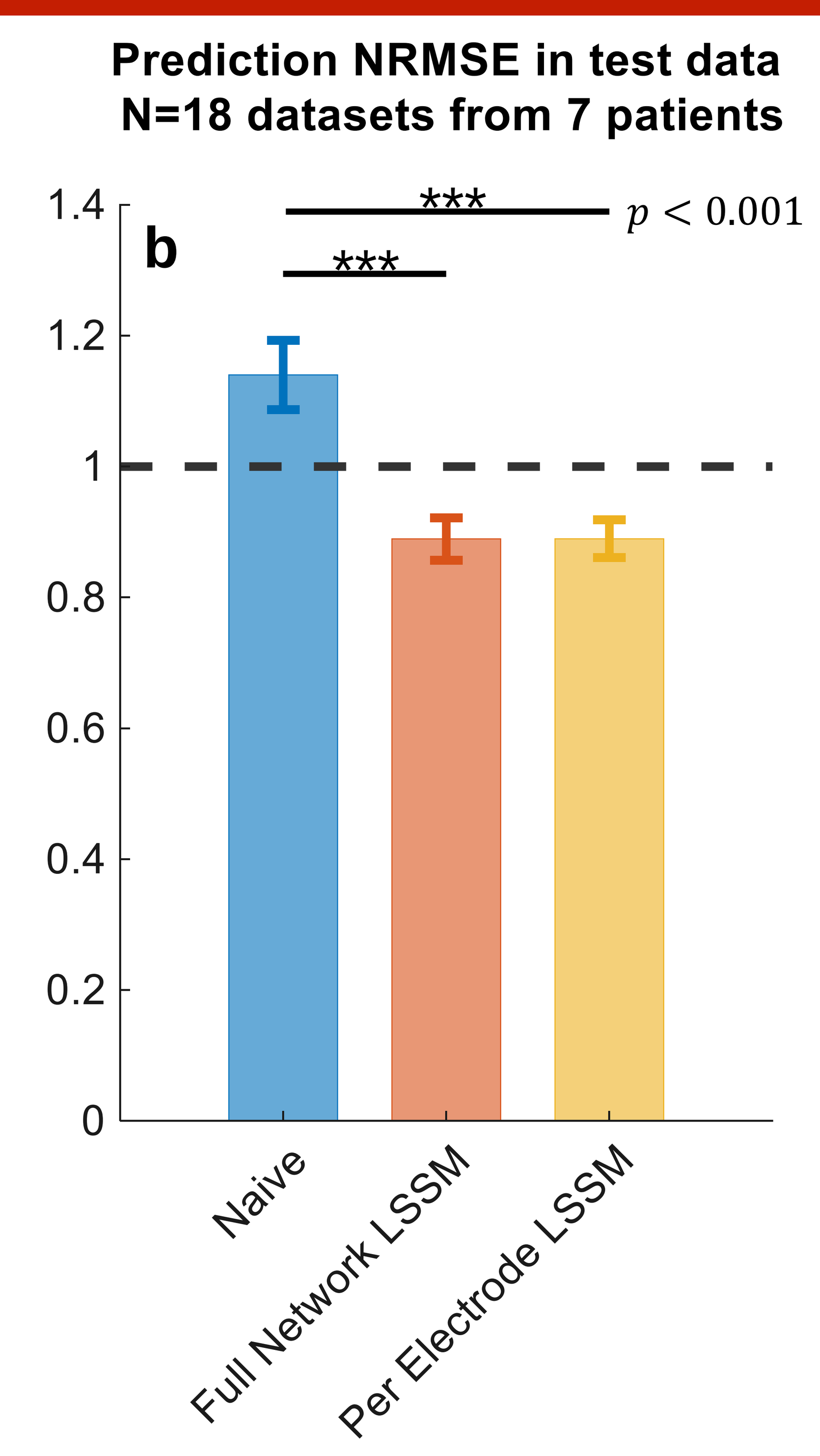
- Identified LSSM order was significantly lower than the number of features (a)
- When every electrode was modeled separately, sum of the order of identified LSSMs was significantly higher (a)

2. Prediction error

- One step ahead prediction error of the model is significantly lower than Naïve or mean prediction (b)
- Sample prediction for a well predicted feature in a test fold is shown below (c)







IV. Conclusions

- Linear state-space model (LSSM) captures the neural feature dynamics through a low dimensional hidden state
- LSSM is significantly more predictive than Naïve or mean predictor
- Full network LSSM achieves prediction error comparable to that of per electrode LSSMs but using significantly lower total order

omid.ghasemsani@usc.edu

Neural Systems Engineering & Information Processing Lab (NSEIP Lab)

UCSF University of California San Francisco

Ming Hsieh Institute
Ming Hsieh Department of Electrical Engineering