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State-Space Modeling of Brain Network Dynamics



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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)

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).

2. Neural Features

sample electrode placement

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

In this work we use an LSSM as follows to model the spontaneous brain activity:

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

- $\square y_t: \text{Neural features extracted from the neural signals}$
- $\square x_t: An abstract hidden state representing the state of the brain$

Reference

[1] P. Van Overschee and B. De Moor, SubspaceIdentification for Linear Systems. Boston, MA: SpringerUS, 1996.

One step ahead prediction error is defined as:

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

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

$$\widehat{y}_{t_{\text{Naïve}}} = y_{t-1}$$

Prediction performance for the *i*th feature is quantified using Normalized Root Mean Square Error:

NRMSE⁽ⁱ⁾ =
$$\sqrt{\frac{\frac{1}{N}\sum_{k=1}^{N} (\hat{y}_{k}^{(i)} - y_{k}^{(i)})^{2}}{var(y^{(i)})}}$$

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



JCcc

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 above 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

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