DYNAMIC SYSTEM IDENTIFICATION FOR GUIDANCE OF STIMULATION PARAMETERS IN HAPTIC SIMULATION ENVIRONMENTS

Andac Demir[1], Safaa Eldeeb[2], Murat Akçakaya[2], Deniz Erdoğmuş[1]

[1]SPIRAL Group, Department of Electrical and Computer Engineering, Northeastern University, Boston, MA 02115, USA

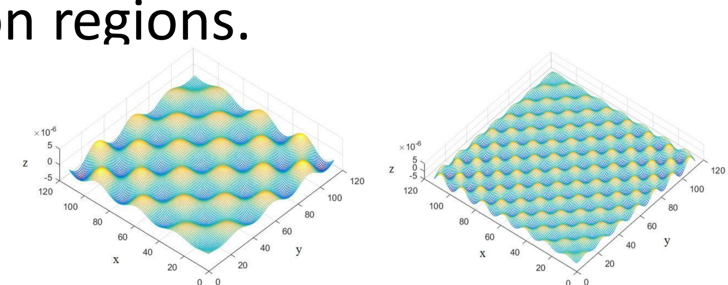
[2]Electrical and Computer Engineering Department, University of Pittsburgh, Pittsburgh, PA 15260, USA

INTRODUCTION

We develop a dynamic system identification model to identify relationships among simultaneously recorded electroencephalography (EEG), electromyography (EMG) and force signals measured from 12 participants performing haptic interactions with 3D printed surfaces having different textures. In the first stage, we solve for the maximum likelihood (ML) parameter vector of a vector autoregression model (VAR) to estimate the latency between endogenous time variables. In the second stage, we explore the modality dependencies between synchronized EEG, EMG and haptic interactions by training VAR models of the same structure.

METHOD

Data Collection: EEG was recorded from 12 right-handed healthy participants according to the 10-20 system from 14-channels, using electrodes placed over the frontal and somatosensory cortex focusing around the sensorimotor integration regions.



*Preprocessing: R*ecorded EEG data were digitized with 1200Hz sampling rate. EEG signals were filtered using a 4th order notch filter with corner frequencies of 58 and 62 Hz, and an 8th order bandpass filter with corner frequencies of 2 and 62 Hz.

Given signals from 14 EEG and 4 EMG channels and force measurements from x, y and z dimensions, a VAR model of order P is,

$$y_t = v + A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t$$

$$y_t \in \mathbb{R}^{K\times 1},\;\; v \in \mathbb{R}^{K\times 1},\;\; A_i \in \mathbb{R}^{K\times K}\;\forall i,\;\; u_t \in \mathbb{R}^{K\times 1}$$

$$\mathrm{E}(u_t) = 0, \quad \mathrm{E}(u_t u_\tau^{'}) = \begin{cases} \Omega & t = \tau \\ 0 & t \neq \tau \end{cases}$$

$\Omega \in \mathbb{R}^{K\times K}$ denotes the covariance matrix and it is positive semidefinite.

A VAR(p) model can be written more compactly as,

$$Y = BZ + U, \quad \text{where:}$$

$$Y := (y_1, \ldots, y_T) \in \mathbb{R}^{K\times T}$$

$$B := (v, A_1 \ldots, A_p) \in \mathbb{R}^{K\times(Kp+1)}$$

$$Z_t := (1, y_{t-1}, \ldots, y_{t-p}) \in \mathbb{R}^{(Kp+1)\times 1}$$

$$Z := (Z_0, \ldots, Z_{T-1}) \in \mathbb{R}^{(Kp+1)\times T}$$

$$U := (u_1, \ldots, u_T) \in \mathbb{R}^{K\times T}$$

The samples of the endogenous multivariate time data are drawn from a Gaussian distribution at each time index,

$$f_{Y_t|Y_{t-1},\ldots,Y_{t-p}}(y_t|y_{t-1},\ldots,y_{t-p};\theta) =$$

$$\mathcal{N}(v + A_1 y_{t-1} + \cdots + A_p y_{t-p}, \Omega) =$$

$$(2\pi)^{-\frac{K}{2}} |\Omega^{-1}|^{\frac{1}{2}} \exp(-\frac{1}{2}(y_t - BZ_t)^{'} \Omega^{-1}(y_t - BZ_t$$

for a likelihood parameter vector defined as,

$$\theta = (v^{'}, \mathrm{vec}(A_1)^{'}, \mathrm{vec}(A_2)^{'}, \ldots, \mathrm{vec}(A_p)^{'}, \mathrm{vech}(\Omega)^{'})^{'}.$$

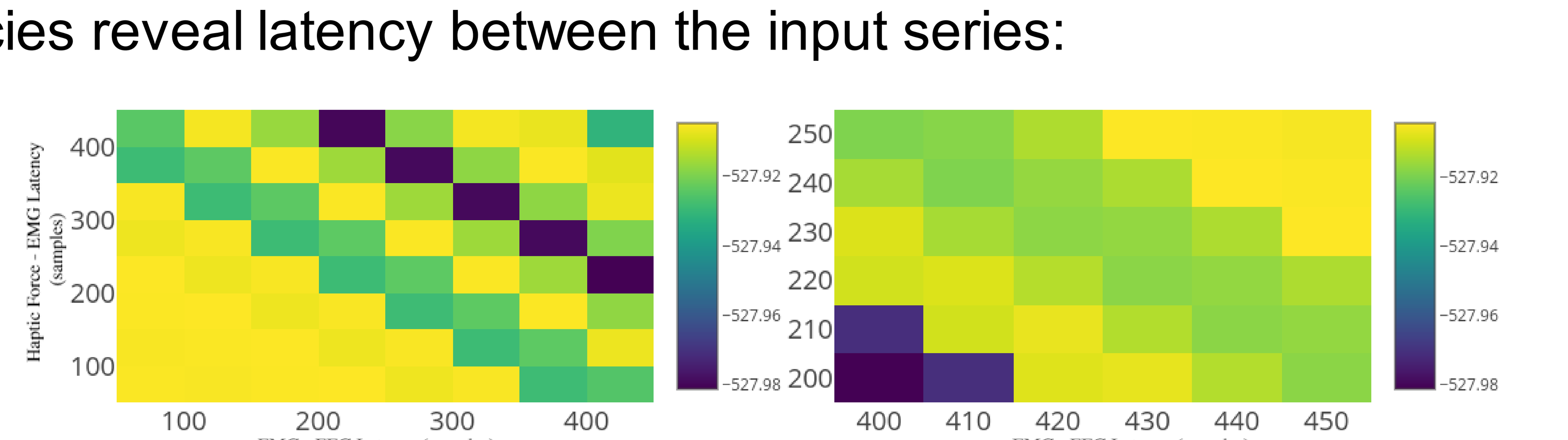
Hence, the log likelihood function is,

$$\ell(\theta|y_t) = -\frac{KT}{2}\ln(2\pi) + \frac{T}{2}\ln|\Omega^{-1}| - \frac{1}{2}\sum_{t=1}^{T}(y_t - BZ_t)^{'}\Omega^{-1}(y_t - BZ_t)$$

We solve for the ML parameter vector of the autoregression model as,

$$\hat{\Omega}_{\mathrm{ML}} = \frac{1}{T}\sum_{t=1}^{T}(y_t - \hat{B}_{\mathrm{ML}} Z_t)(y_t - \hat{B}_{\mathrm{ML}} Z_t)^{'}$$

Heatmaps for BIC scores at different haptic force-EMG and EMG-EEG latencies reveal latency between the input series:



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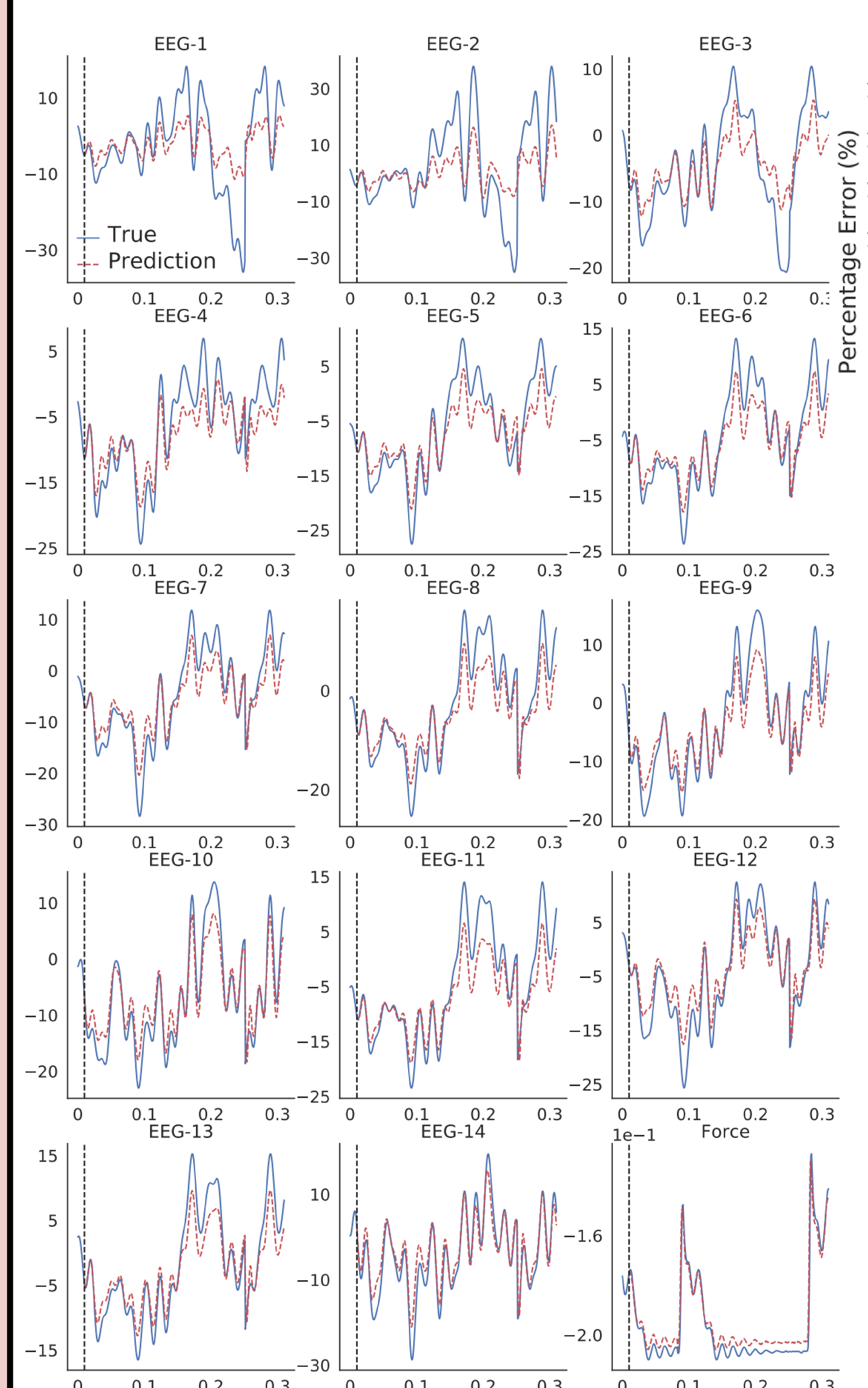
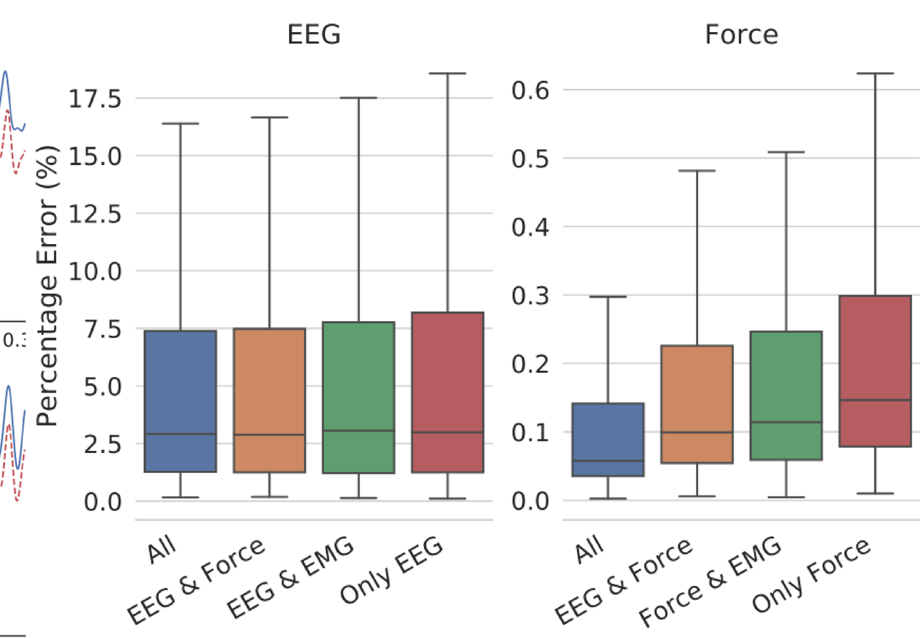
Grid search is utilized to estimate the latency responses that minimize BIC, consequently maximize log likelihood.
After synchronization stage, for each different combination of system input series a model order (lag order) was selected based on BIC scores.

EXPERIMENTS & RESULTS





Bar plots show the percentage error distributions of the predicted EEG and haptic force interactions for each different combination of system input series averaged across all the channels and all the participants in the test set.

Figure shows the actual measurements and one-step-ahead predictions for all of the EEG (µV) channels and force (V) measurements from z-dimension in a time window of 300 ms (360 samples).

Samples before the dotted line, marked at time 0, are the first 17 samples observed and there is no prediction within this time frame.

The major drawback of the proposed linear model is that the mean, variance, and autocorrelations of the original series aren't constant in time, even after detrending. Increasing the number of integration steps helps with stationarizing the time data, but at the cost of losing long term temporal dependencies.

We also conjecture that using a fixed lag order is a bottleneck in improving the precision of predictions.

CONCLUSION

We implement a maximum likelihood approach for fitting a multivariate VAR model to different combination of EEG, EMG, and force signals simultaneously recorded during haptic stimulation. Specifically, we estimate the lag order of the model and the latency between data from different modalities by optimizing the BIC score of the fitted model. Then: (i) we employ the proposed method to quantify the dependencies among the different modalities, and (ii) test the capability of the proposed method in one-step-ahead prediction