A Modal Approach to the Space Time Dynamics of Cognitive Biomarkers

T. Griffith

Defense

April 28, 2022

Outline

1. Introduction & Motivation
2. A Dynamic Systems View of Brain Waves
3. System Identification of Brain Wave Modes Using EEG
4. Modal Analysis of Brain Wave Dynamics
5. Adaptive Unknown Input Estimators
6. Reconstructing the Brain's Unknown Input
7. Conclusions

1. Introduction & Motivation

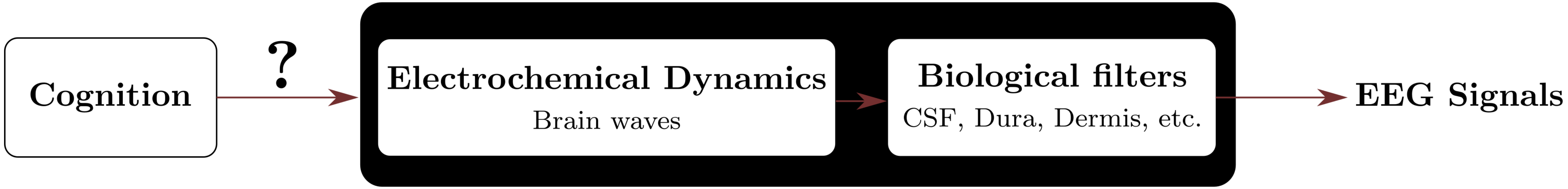


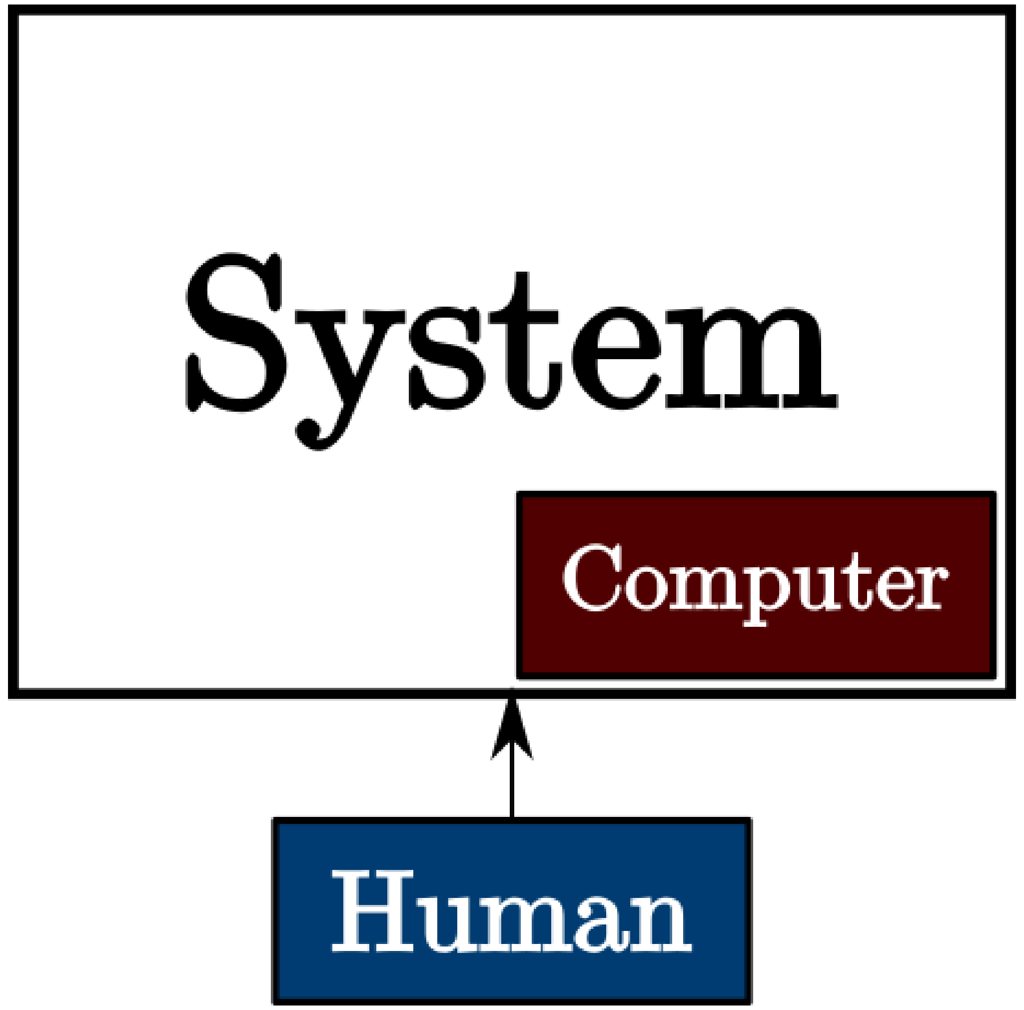
Fig 1. A Wholistic View of Brain Waves

Hogarth de la Plante, Unsplash

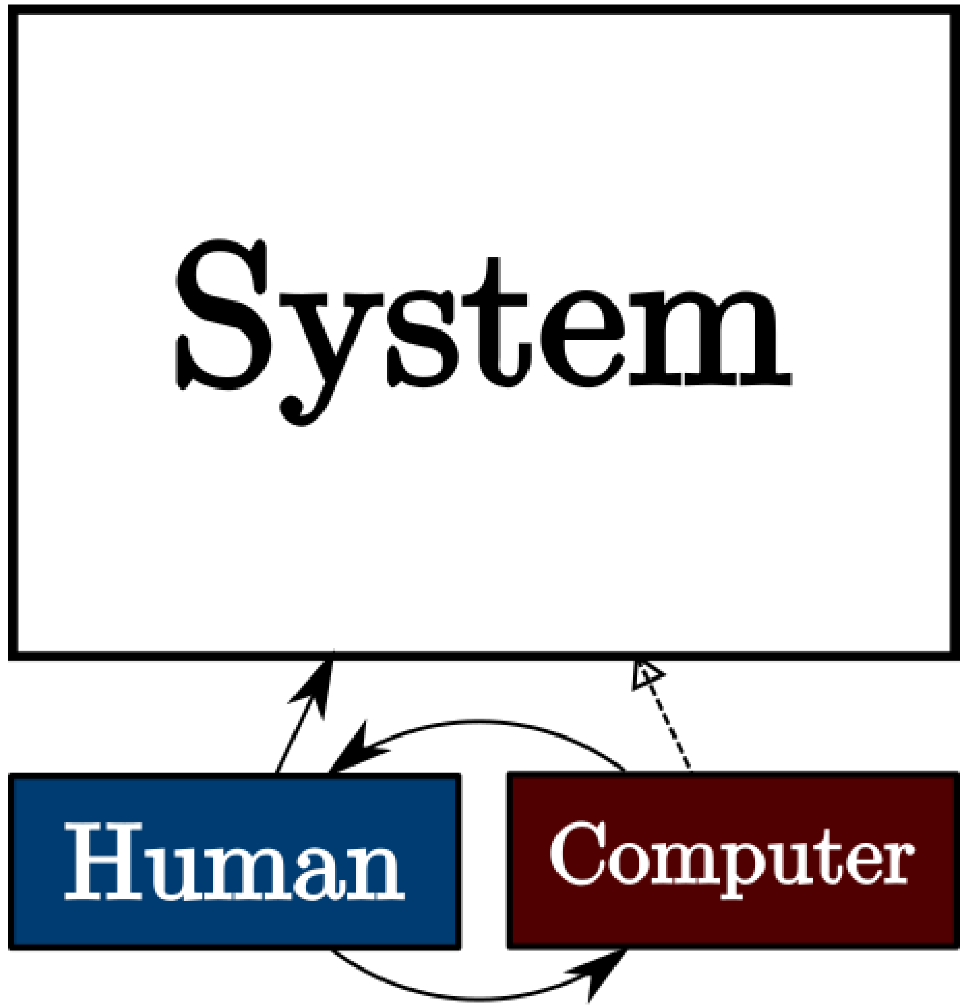
Clinical and HMI Applications

Spencer Lowell, Wired, 2021

Shared flow of information is implied



The computer as part of the system



The computer as a teaming member

State of the art: surveys and orthogonal bases

> *Recent modeling work, however, using large-scale dynamical models on the human connectome, suggests that cortical flow patterns are multistable and exhibit phase-transitions. To study such phenomena, a dynamic analysis in which no assumptions about stationarity are made, is required.*

Hindriks, Rikkert, et al. “Latency analysis of resting-state BOLD-fMRI reveals traveling waves in visual cortex linking task-positive and task-negative networks.” Neuroimage 200 (2019): 259-274.

Novel potential

> *There has been a recent proliferation of more rugged and durable sensor devices (e.g., fNIRS sensors) that can be used while people take part in ecologically valid activities to assess changes in neurophysiology, physiology, and behavior that correlate with cognitive state. In addition, recent advances in machine learning and modeling techniques can be used to interpret information about human states (e.g., SA) from noisy data acquired in such environments that previously was unusable.*

Bracken, B., Tobyne, S., Winder, A., Shamsi, N., & Endsley, M. R. (2021, July). Can Situation Awareness Be Measured Physiologically?. In International Conference on Applied Human Factors and Ergonomics (pp. 31-38). Springer, Cham.

There is a demonstrated need for improved models of neural biomarkers that consider **nonstationary spatio-temporal dynamics** jointly.

- Rigorous
- Transparent
- Non-invasive
- Physiological

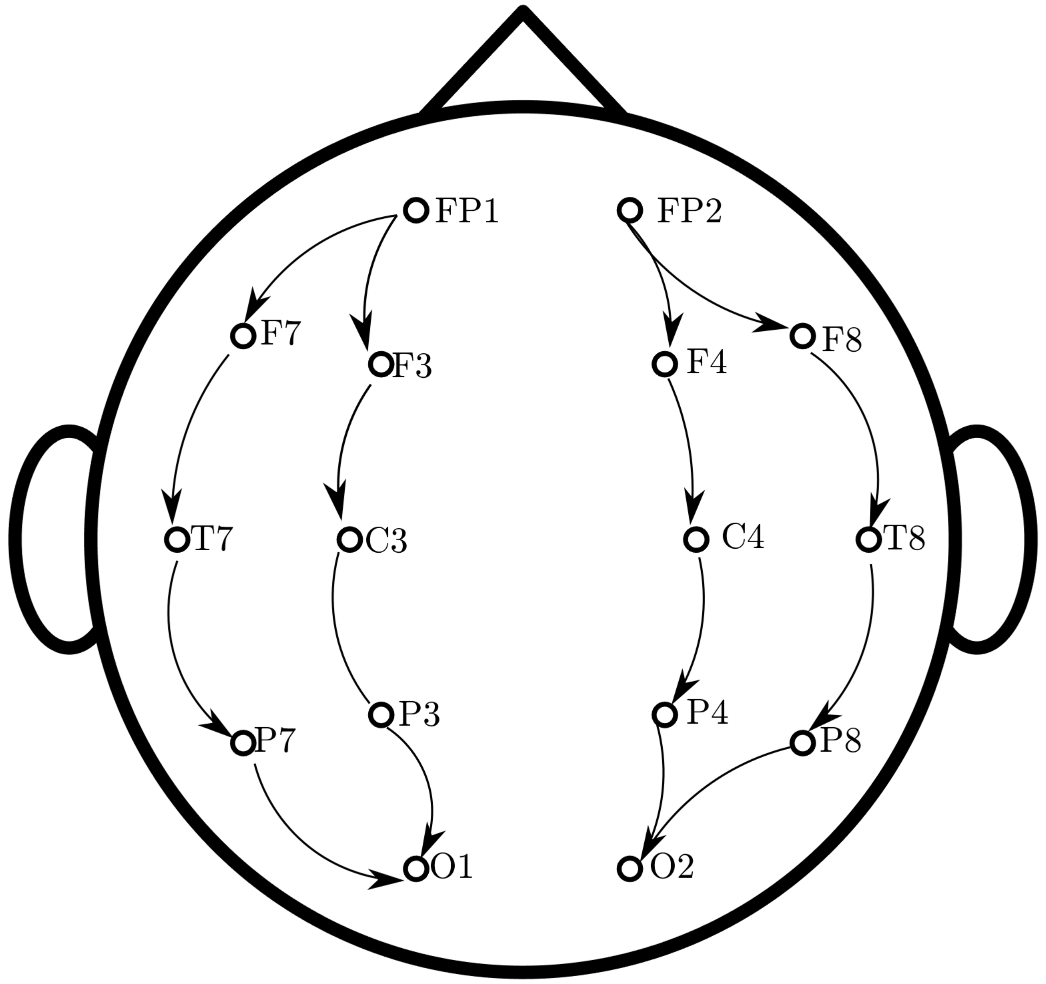
Modeling considerations

- Local vs. **Whole**
- Linear vs. **Nonlinear**
- **Individual** vs. Population
- Static vs. **Dynamic**
- Offline vs. **Online**
- Parametric vs. **Nonparametric**

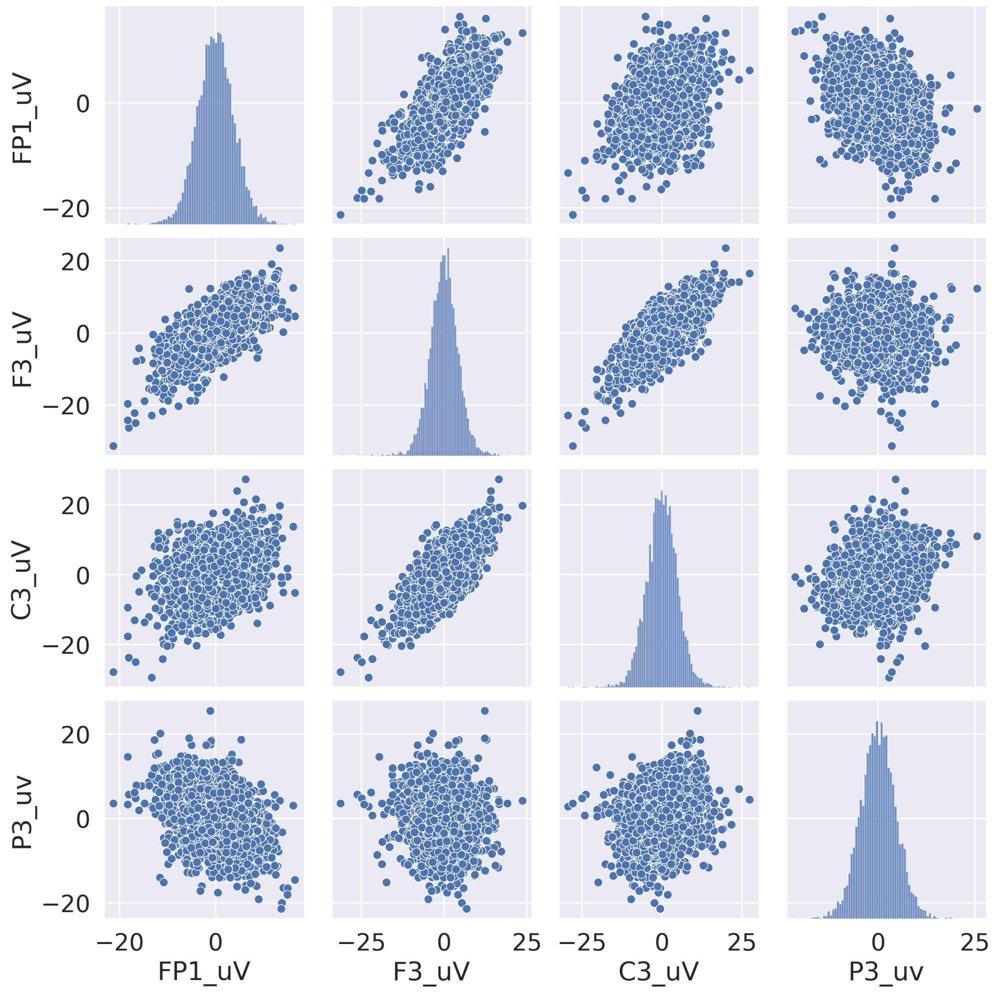
2. A Dynamic Systems View of Brain Waves

Characteristics of EEG

- EEG is only loosely tied to outcomes
- Linear, nonlinear, and noise
- Channel cross talk
- Variety of referencing techniques

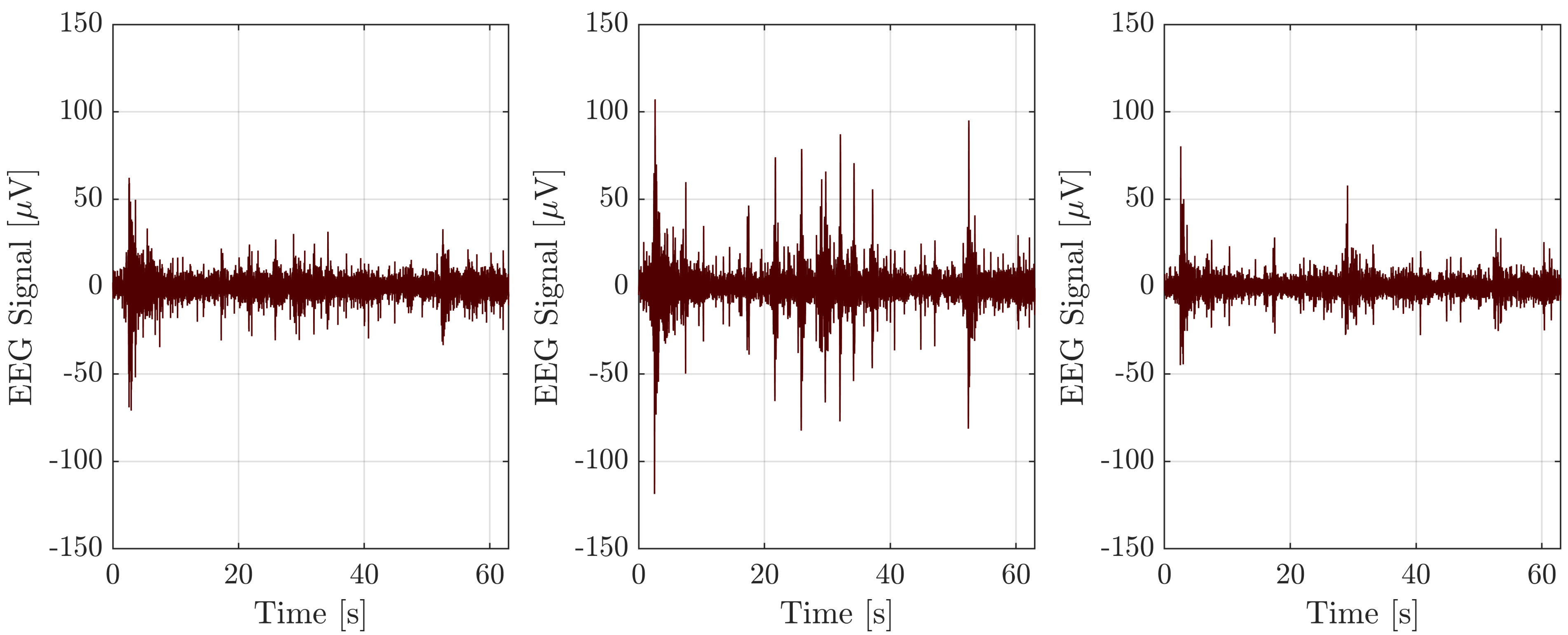


Longitudinal referencing



EEG channel pair plots

A cannonical approach:



True brain wave plant: $\begin{cases} \dot{x} = Ax + Bu + v_x \\ y = Cx \end{cases}$

where $A,\ B,\ C,\ v_x,\ x,$ and u are all unknown.

This level of uncertainty is an unsovled problem

Identify the plant: $\begin{cases} \dot{x}_m = A_m x + v_x \\ y_m = C x_m \end{cases}$,

accepting the uncertainty in A_m.

Treating nonlinear effects

PHYSICAL REVIEW E **67**, 046204 (2003)

Indications of nonlinear structures in brain electrical activity

Temujin Gautama,* Danilo P. Mandic,† and Marc M. Van Hulle‡
Laboratorium voor Neuro- en Psychofysiologie, K.U. Leuven, Campus Gasthuisberg, Herestraat 49, B-3000 Leuven, Belgium
(Received 6 August 2002; revised manuscript received 23 January 2003; published 10 April 2003)

Capturing time-varying brain dynamics

Klaus Lehnertz[1,2,3,*], Christian Geier[1,2], Thorsten Rings[1,2], and Kirsten Stahn[1,2]

[1] Department of Epileptology, University of Bonn, Sigmund-Freud-Straße 25, 53105 Bonn, Germany
[2] Helmholtz-Institute for Radiation and Nuclear Physics, University of Bonn, Nussallee 14–16, 53115 Bonn, Germany
[3] Interdisciplinary Center for Complex Systems, University of Bonn, Brühler Straße 7, 53175 Bonn, Germany

Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state

Ralph G. Andrzejak,[1,2,*] Klaus Lehnertz,[1,†] Florian Mormann,[1,2] Christoph Rieke,[1,2] Peter David,[2] and Christian E. Elger[1]
[1]*Department of Epileptology, University of Bonn, Sigmund-Freud-Strasse 25, 53105 Bonn, Germany*
[2]*Institut für Strahlen- und Kernphysik, University of Bonn, Nußallee 14-16, 53115 Bonn, Germany*
(Received 14 May 2001; published 20 November 2001)

Adaptive Unknown Input Brain Wave Estimator:

$$\begin{cases} \dot{\hat{x}} = \big(A_m + BL(t)C\big)\hat{x} + B\hat{u} + K_x e_y; \\ \hat{y} = C\hat{x}. \end{cases}$$

Modes elegantly capture the spatio-temporal dynamics

True brain wave plant

$$\begin{cases} \dot{x} = Ax + Bu + v_x \\ y = Cx \end{cases}$$

Modal brain wave plant

$$\begin{cases} \dot{\eta} = \Lambda\eta + V^{-1}Bu + V^{-1}v_x \\ y = CV\eta \end{cases}$$

Some important analytical properties:

- Frequency
- Damping
- Mode shape
- Complexity

3. System Identification of Brain Wave Modes Using EEG

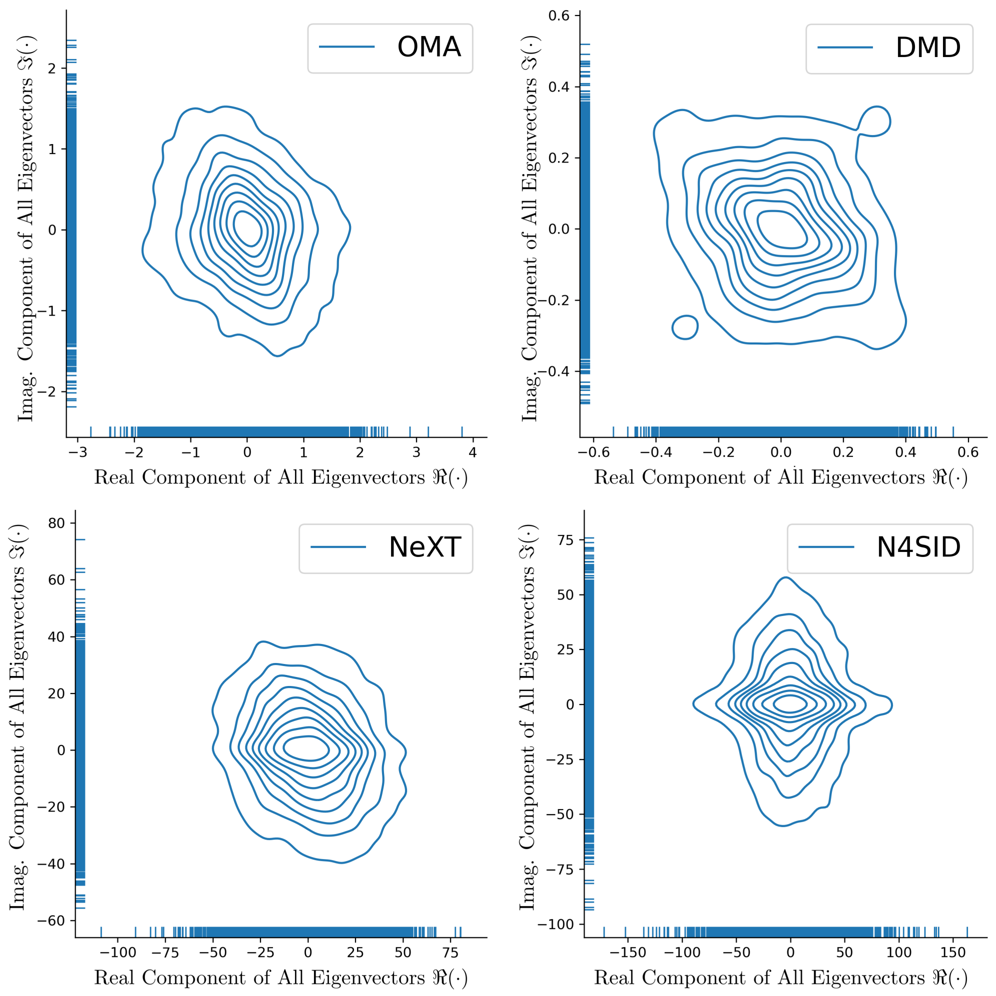
System Identification of Brain Wave Modes Using EEG

Identifying linear patterns

Identify the plant: $$\begin{cases} \dot{x}_m = A_m x + v_x \\ y_m = C x_m \end{cases}$$

Considered algorithms

- **OMA**
- NeXT-ERA
- n4sid
- DMD



System Identification of Brain Wave Modes Using EEG

Identifying linear patterns

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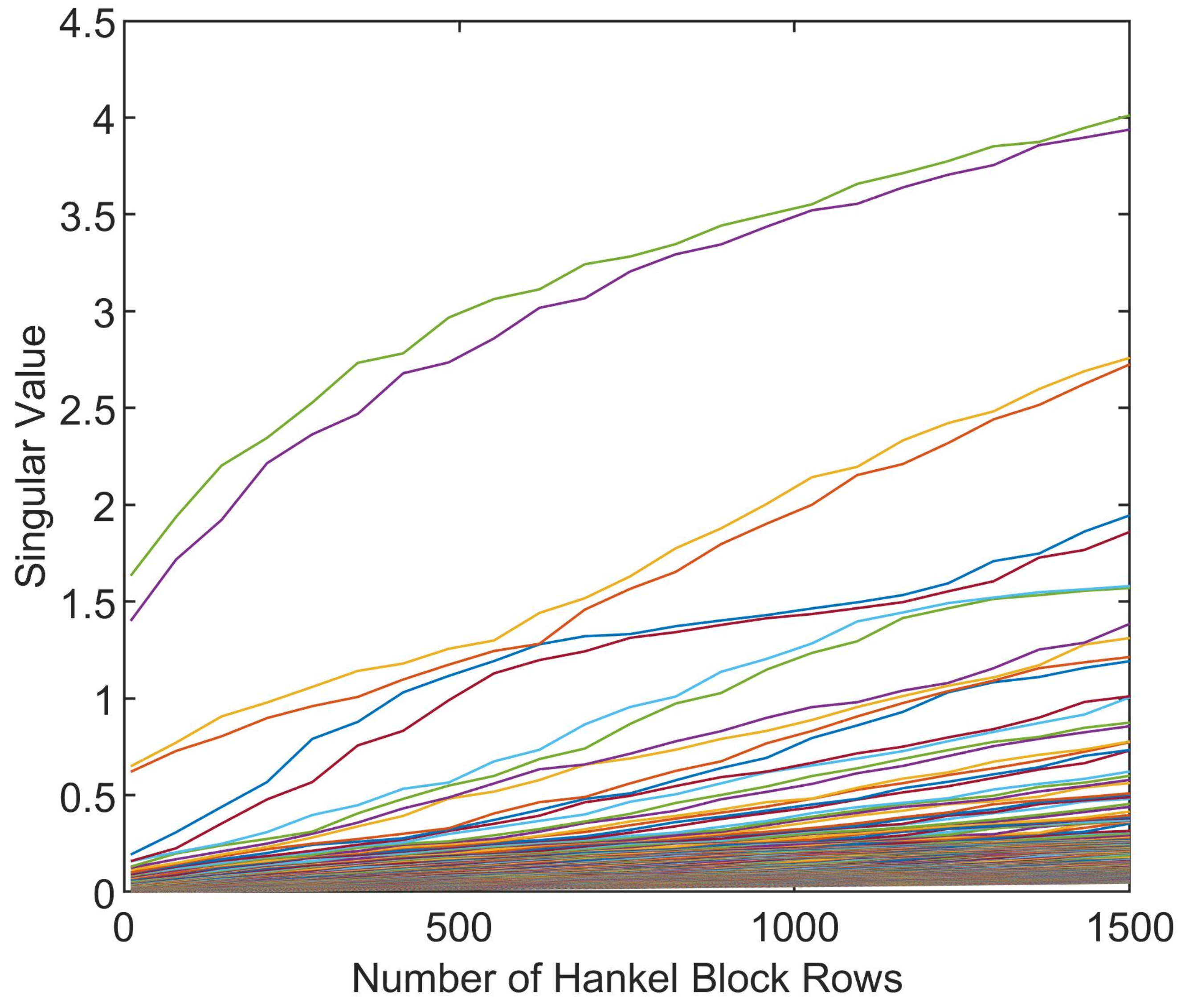
$$O = \begin{bmatrix} C \\ CA_m \\ CA_m^2 \\ \vdots \\ CA_m^{s-1} \end{bmatrix} X_0$$

$$= \Gamma X_0$$

$$\hat{\Gamma} = US^{1/2} \; \hat{X}_0 = S^{1/2} V^*$$



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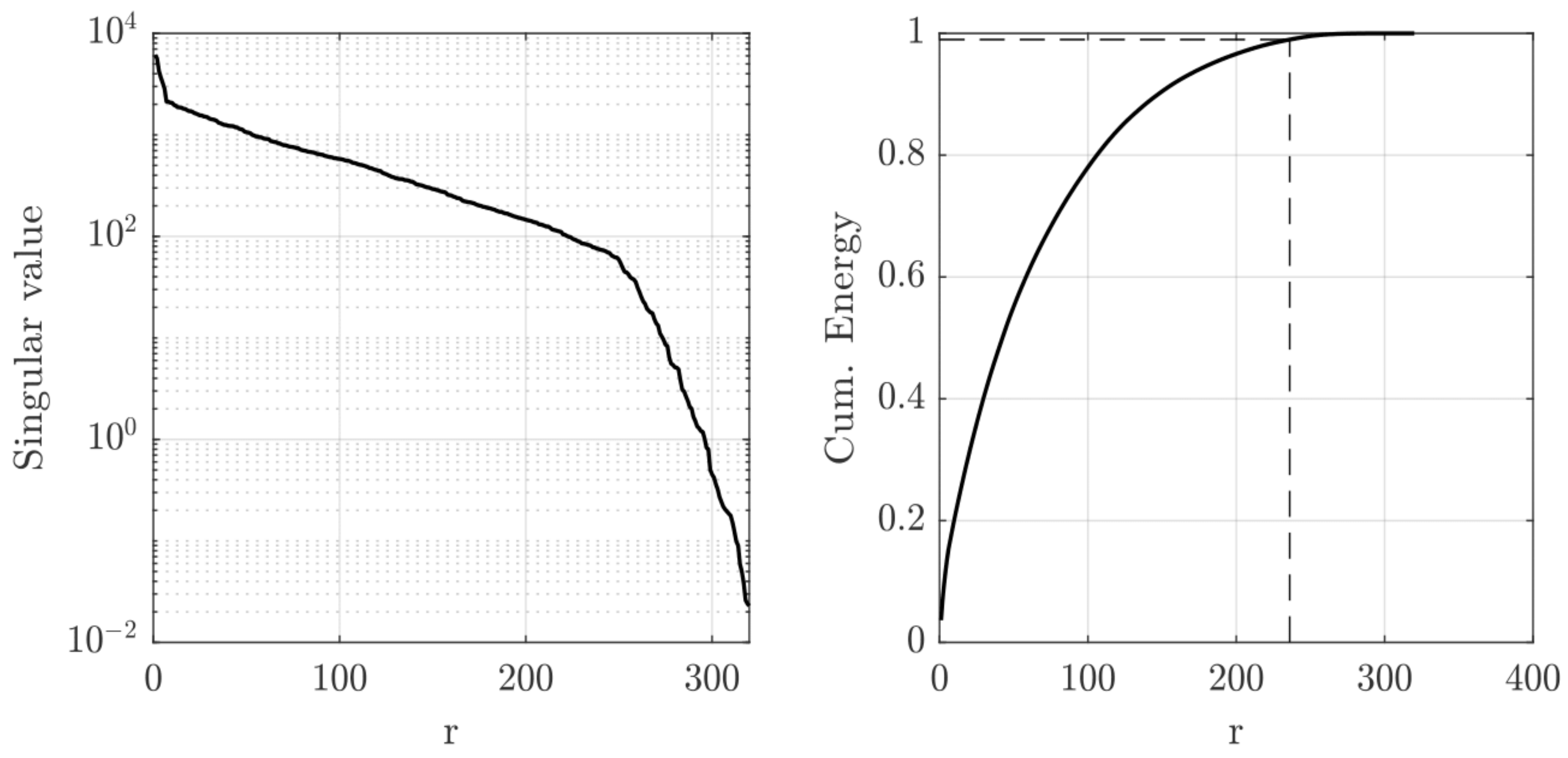

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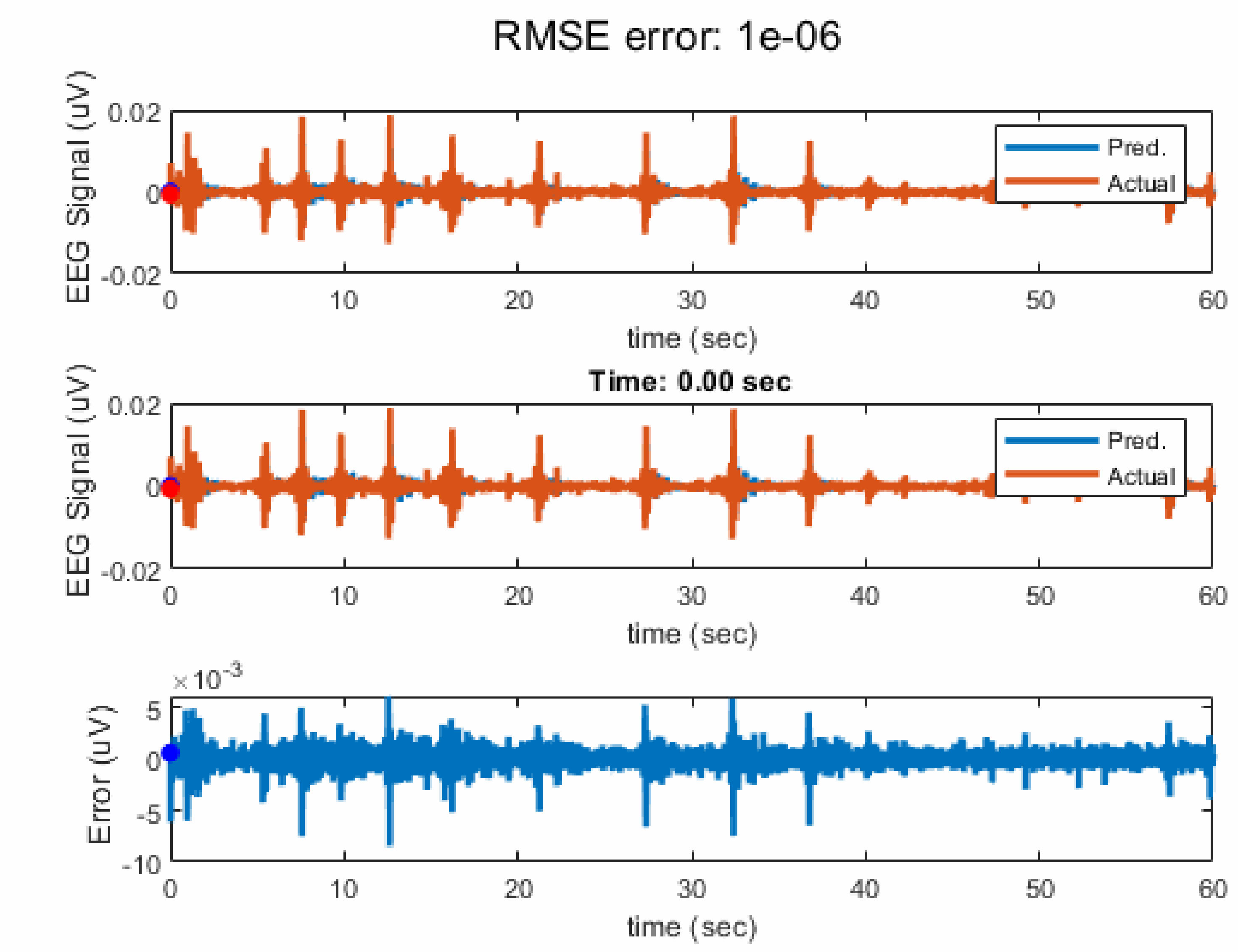

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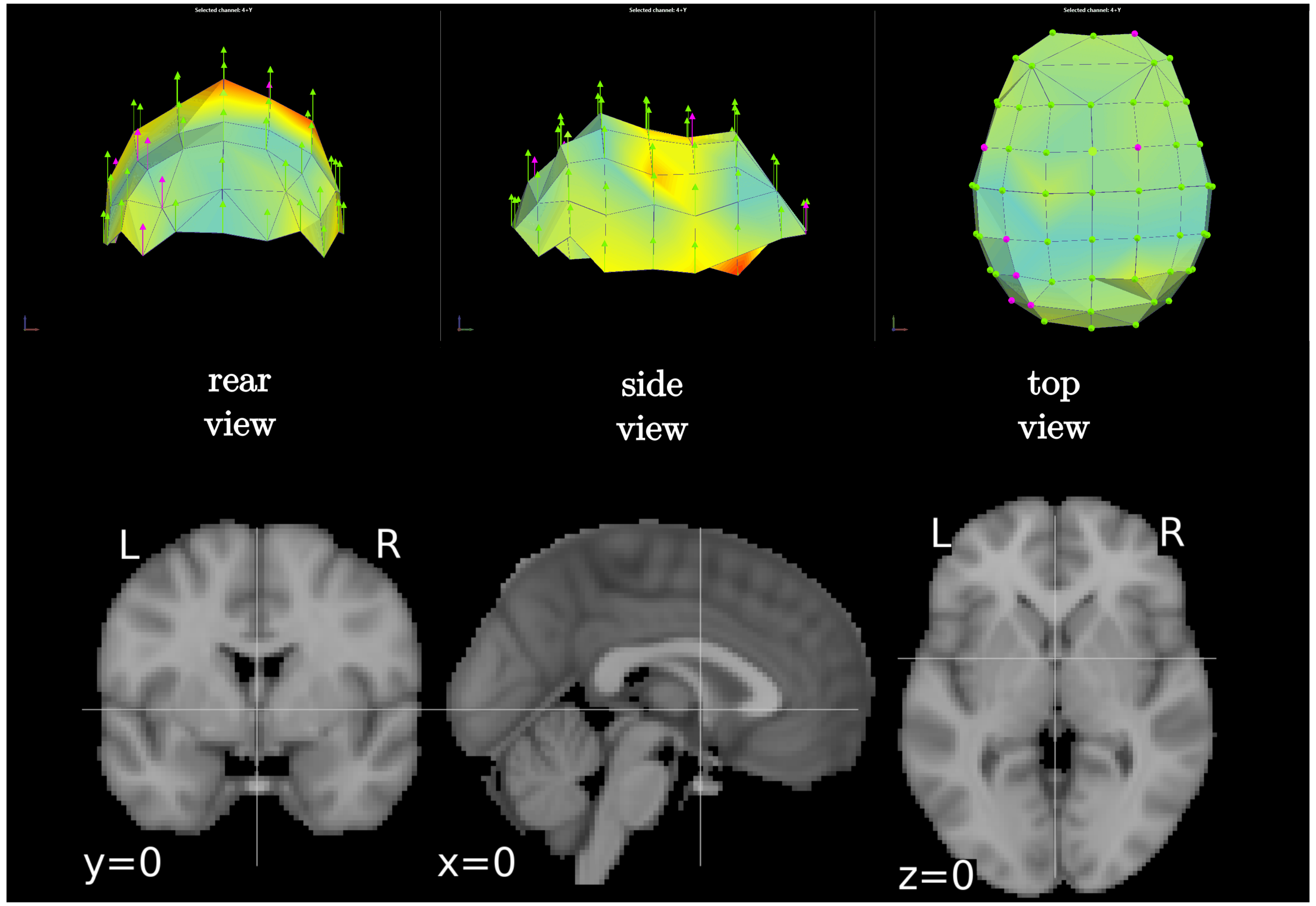

System Identification of Brain Wave Modes Using EEG

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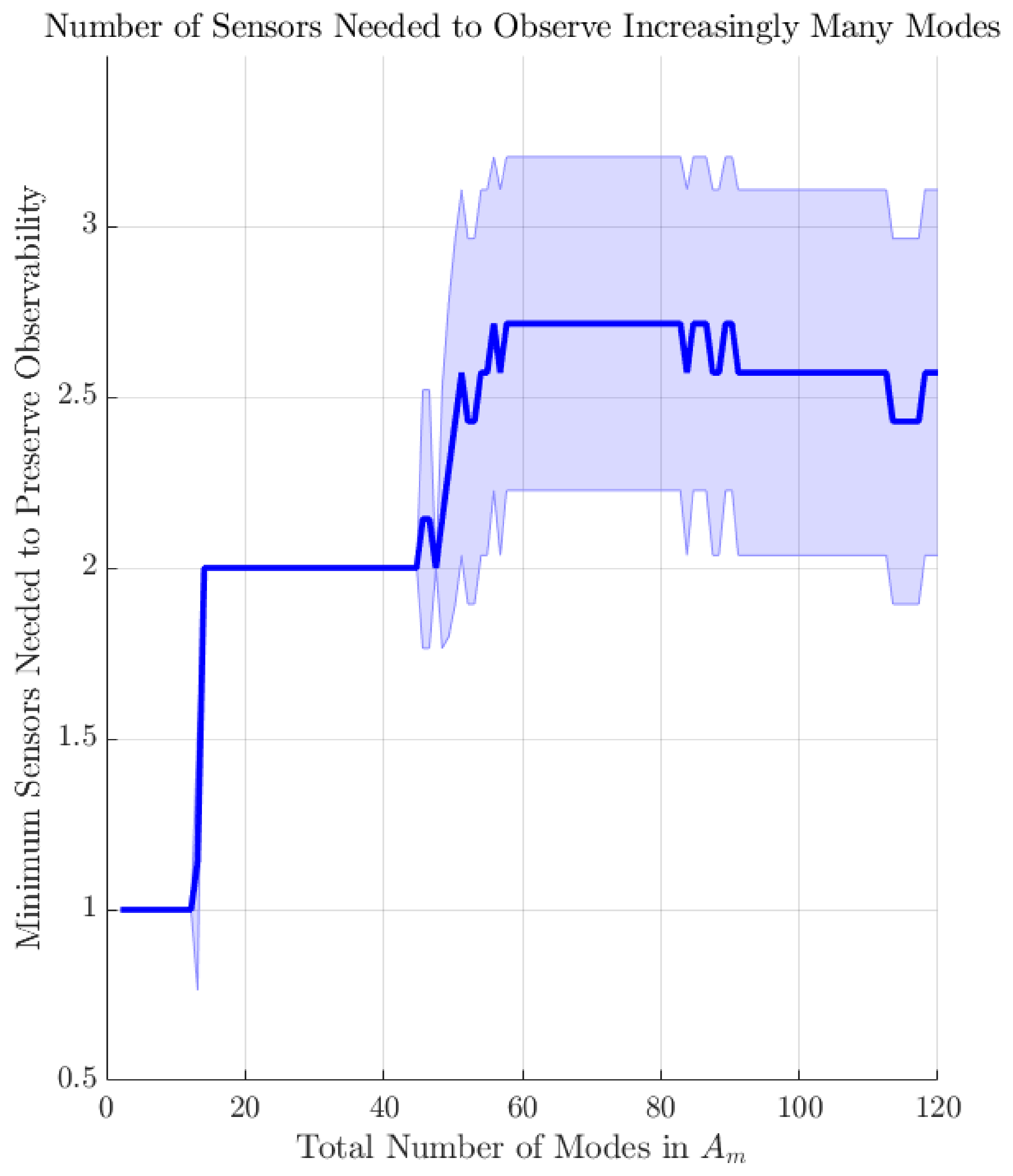
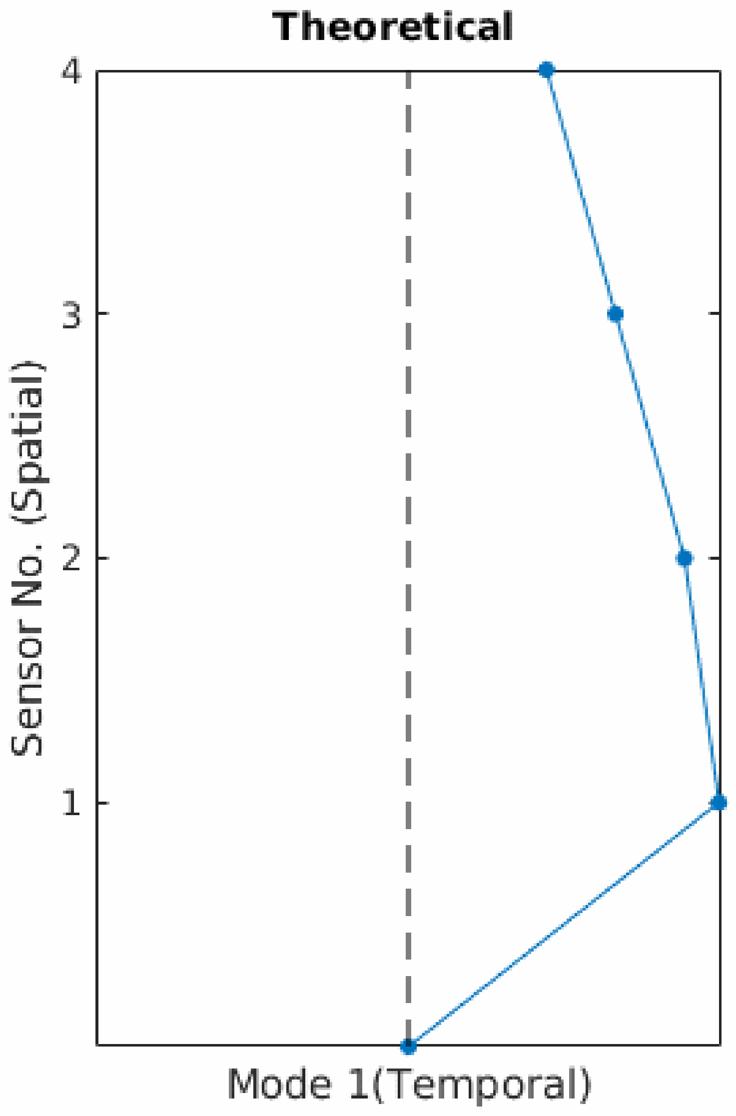
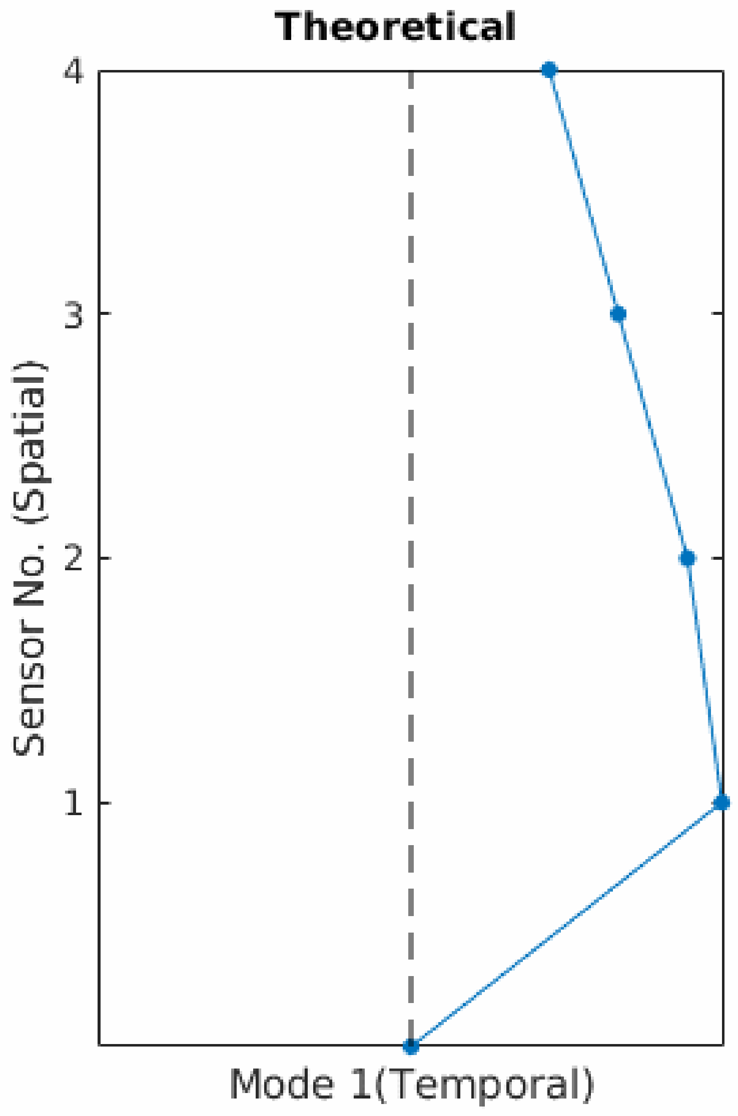


4. Modal Analysis of Brain Wave Dynamics

Modal Analysis of Brain Wave Dynamics

Brain wave modes are traveling and standing





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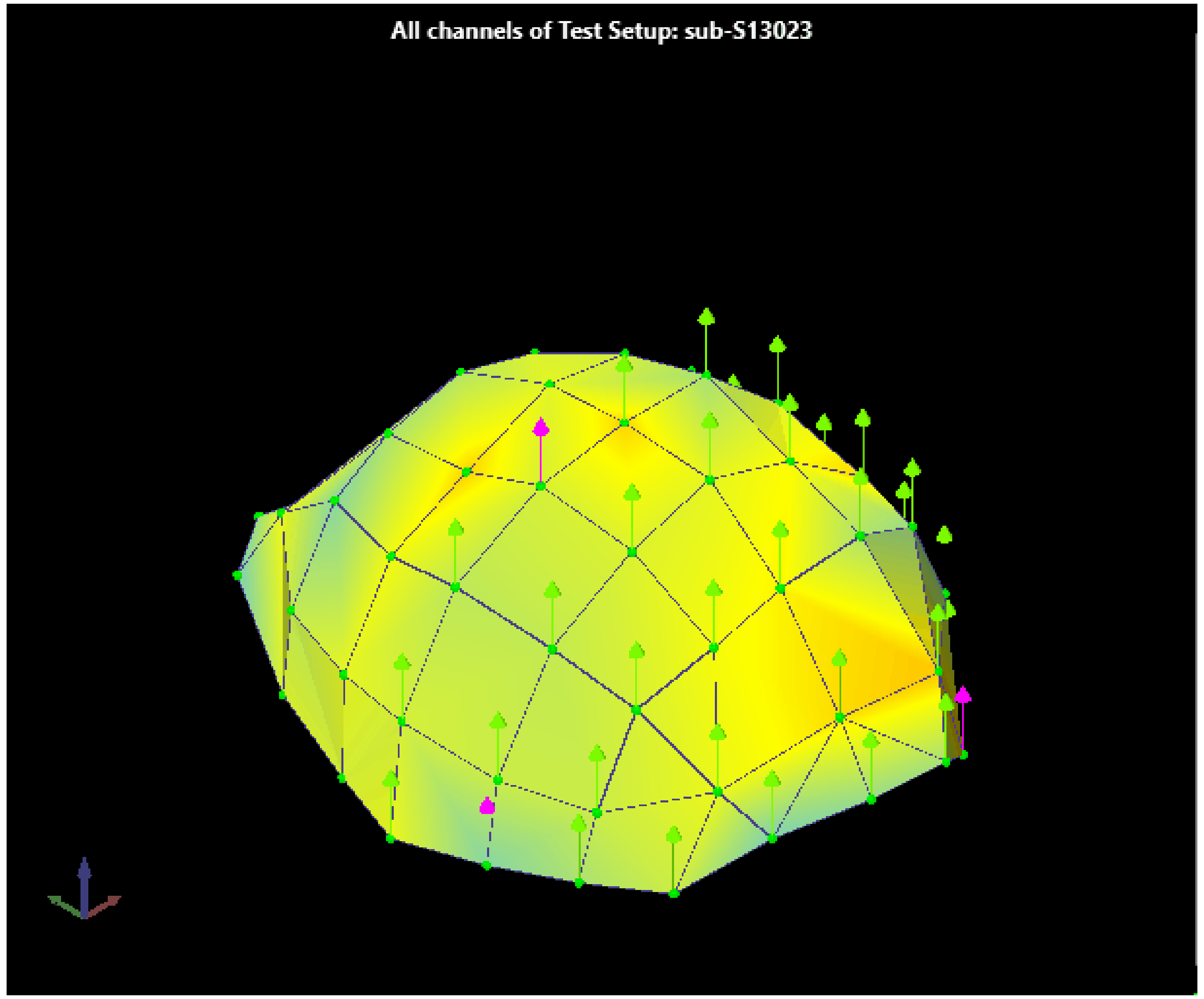
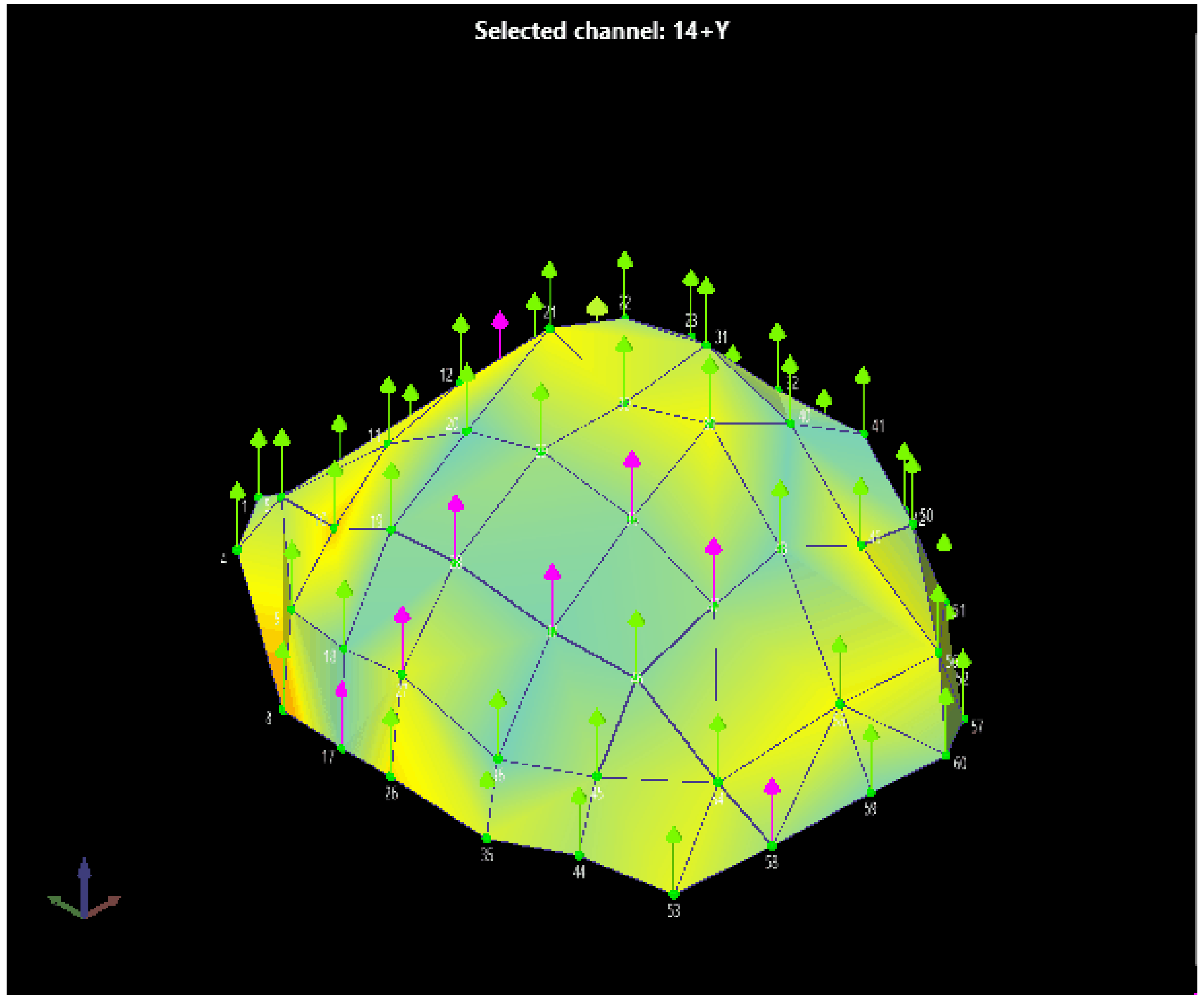
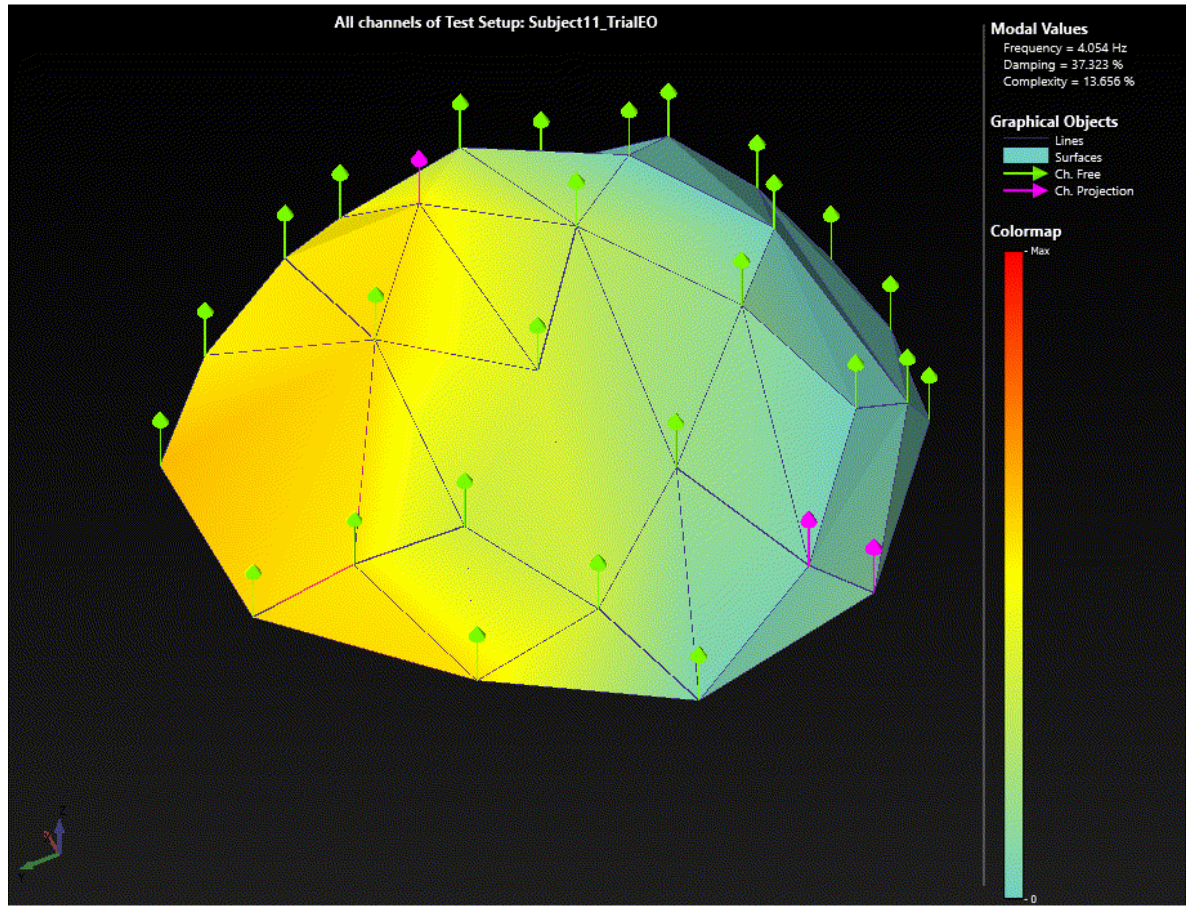
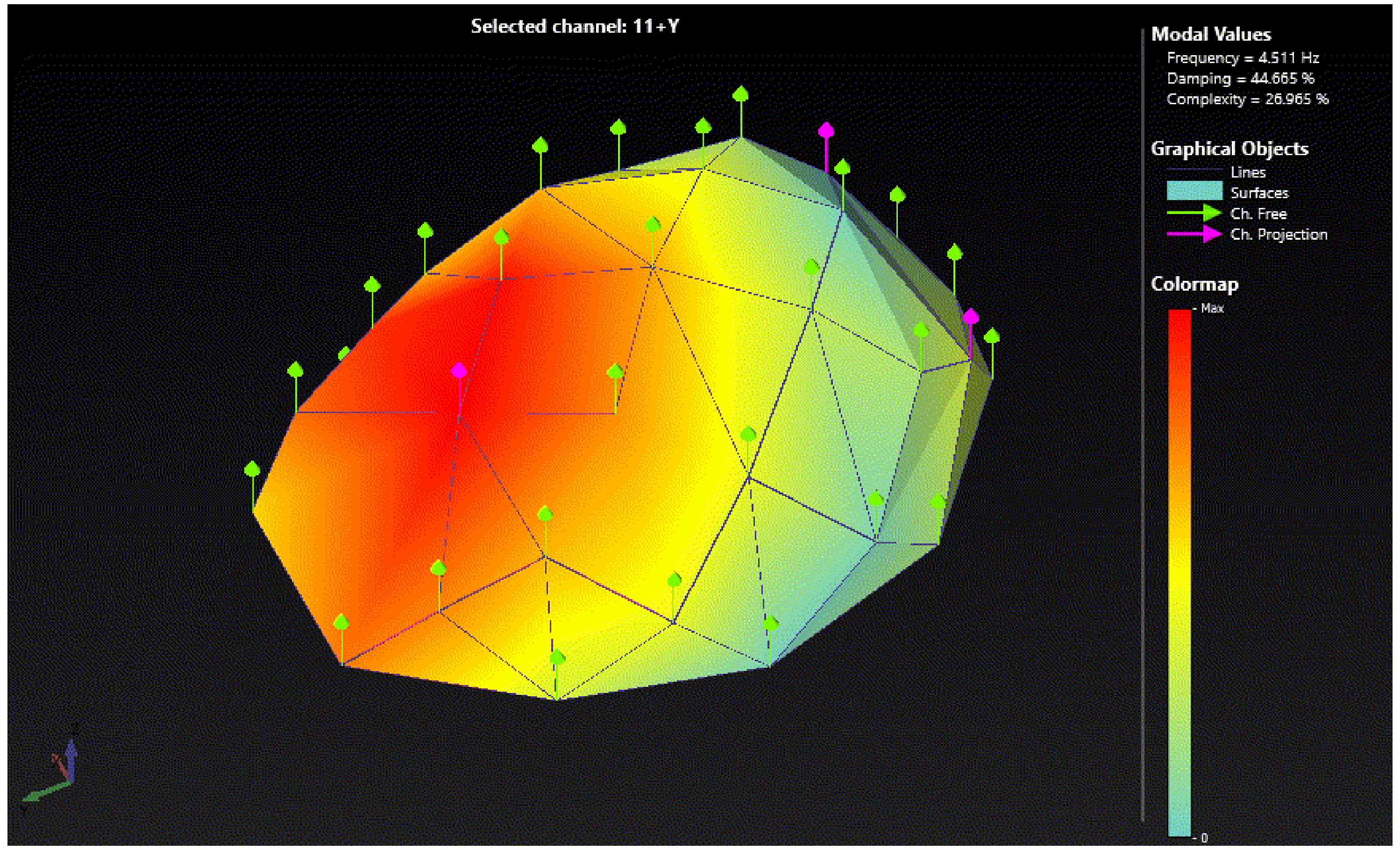




Modal Analysis of Brain Wave Dynamics

Some brain wave modes are task independent

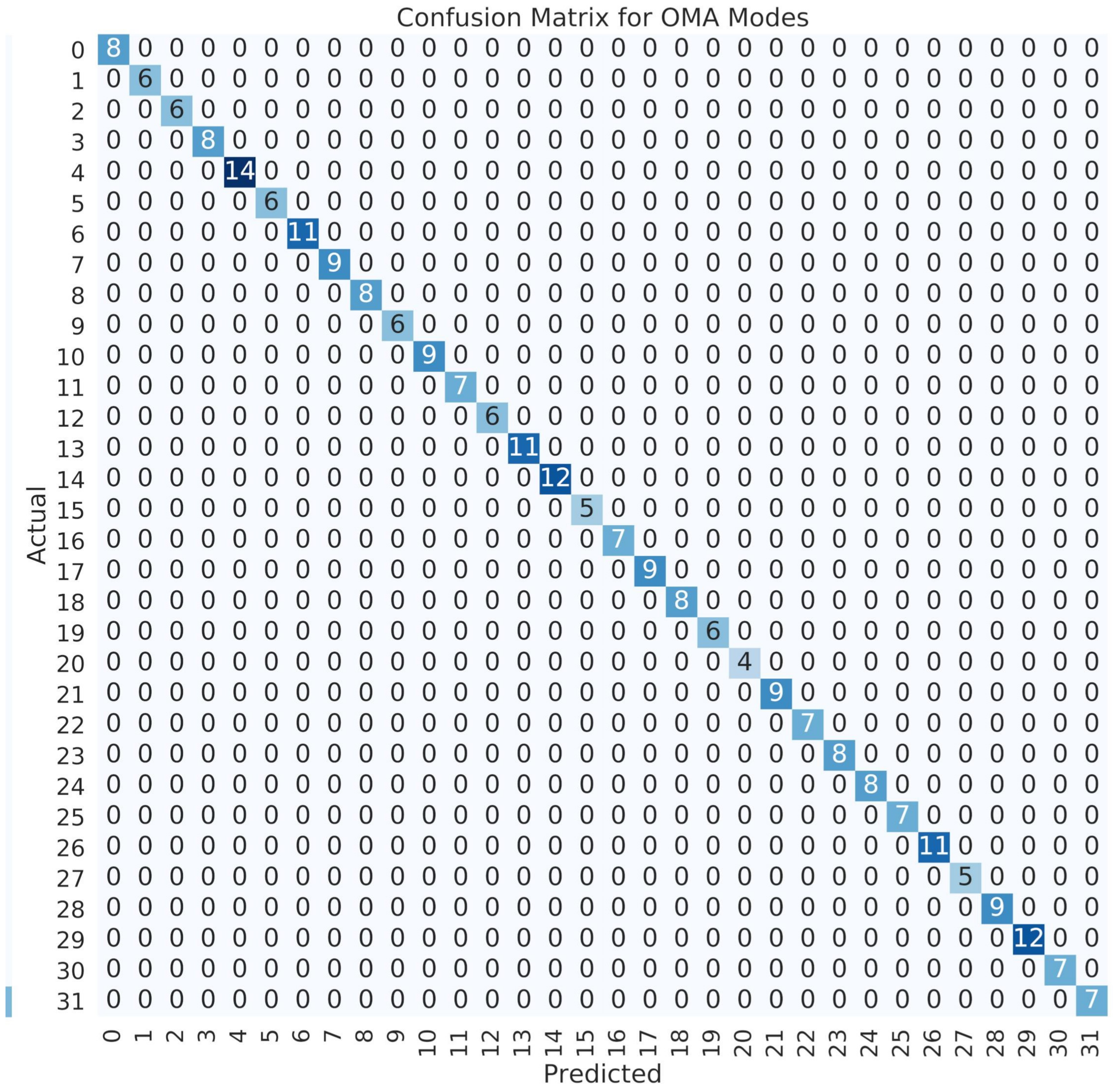




	Frequency	Damping [%]	Complexity [%]	Shape Correl.
Alpha Mode 1	4.34 ± 0.03	8.20 ± 1.20	11.47 ± 17.59	0.97 ± 0.016
Beta Mode 2	21.83 ± 0.22	1.98 ± 2.63	32.29 ± 35.67	0.96 ± 0.018
Gamma Mode 3	40.39 ± 0.26	11.87 ± 7.49	12.42 ± 16.88	0.99 ± 0.010
Gamma Mode 4	44.19 ± 0.24	2.52 ± 1.39	2.93 ± 5.69	0.99 ± 0.012

Modal Analysis of Brain Wave Dynamics

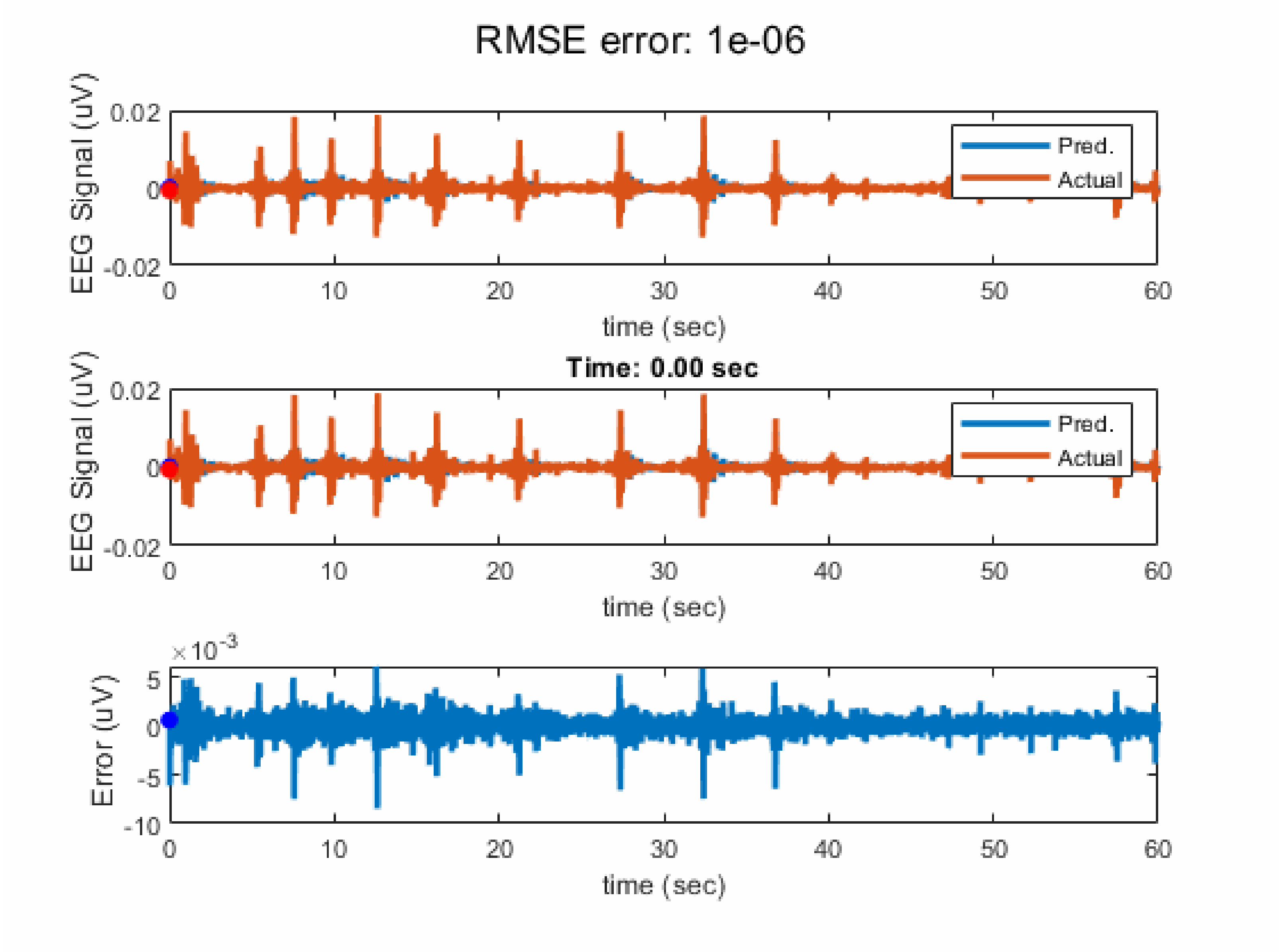
Brain wave modes are interindividual

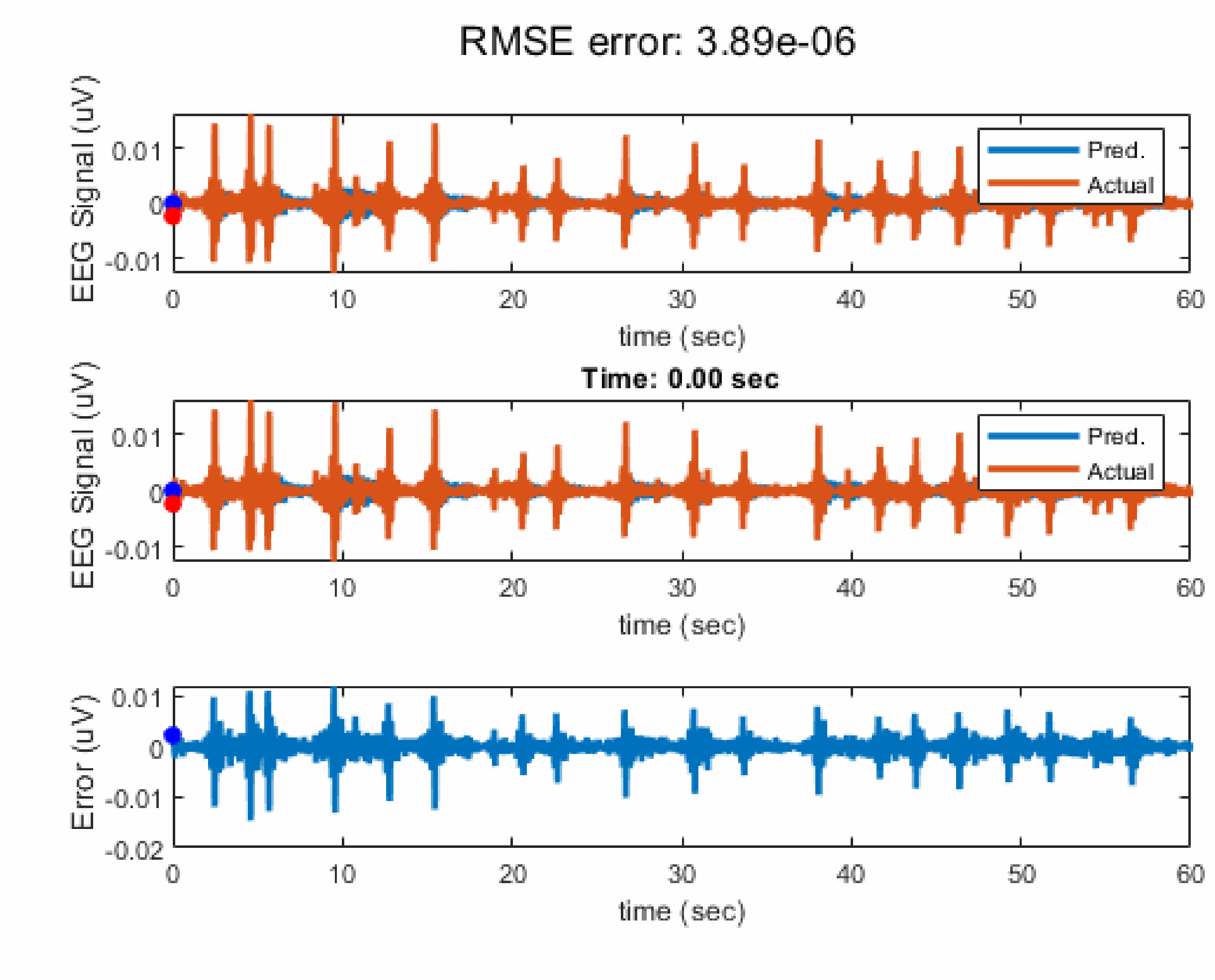


Reference	No. of Electrodes	Accuracy [%]
This work	32	99.85
This work	8	96.45
Wilaiprasitporn et al.	32	99.90
Wilaiprasitporn et al.	5	99.1
DelPozo-Banos et al.	32	97.97

Modal Analysis of Brain Wave Dynamics

Brain wave modes poorly match nonlinear dynamics





5. Adaptive Unknown Input Estimators

Adaptive Unknown Input Estimators

Estimator overview

Three significant uncertainties

- Input u is unknown, external
- State matrix A may have uncertainty
- General process uncertainty v_x

Can we synthesize $\boldsymbol{u}$ and correct $\boldsymbol{A}$?

$$\dot{x} = Ax + Bu + v_x$$
$$y = Cx$$

Adaptive Unknown Input Estimators

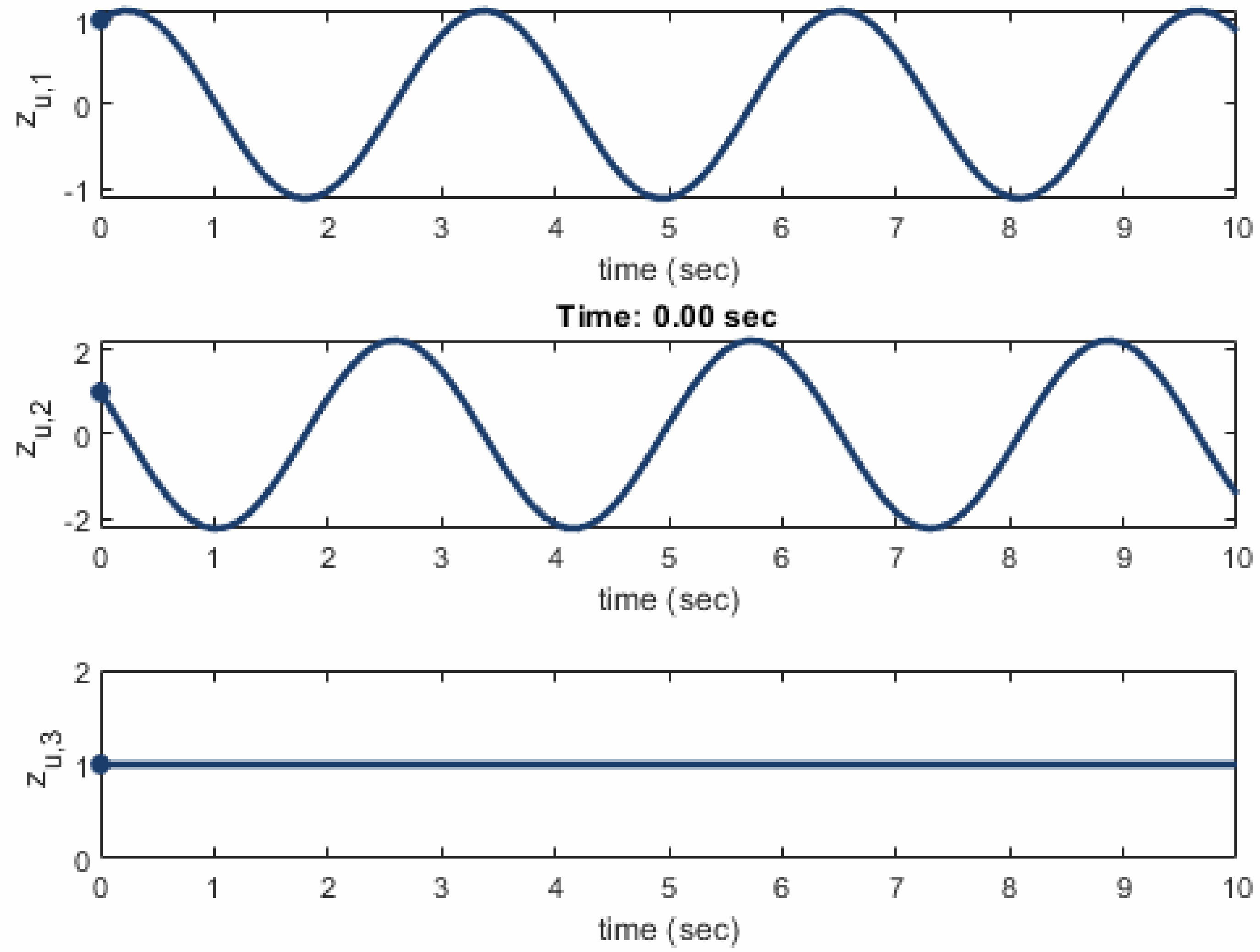
Modeling unknown inputs

Approximate input space $\mathbb{U}$

- $\hat{u} = \sum_{i=1}^{N} c_i f_i(t)$

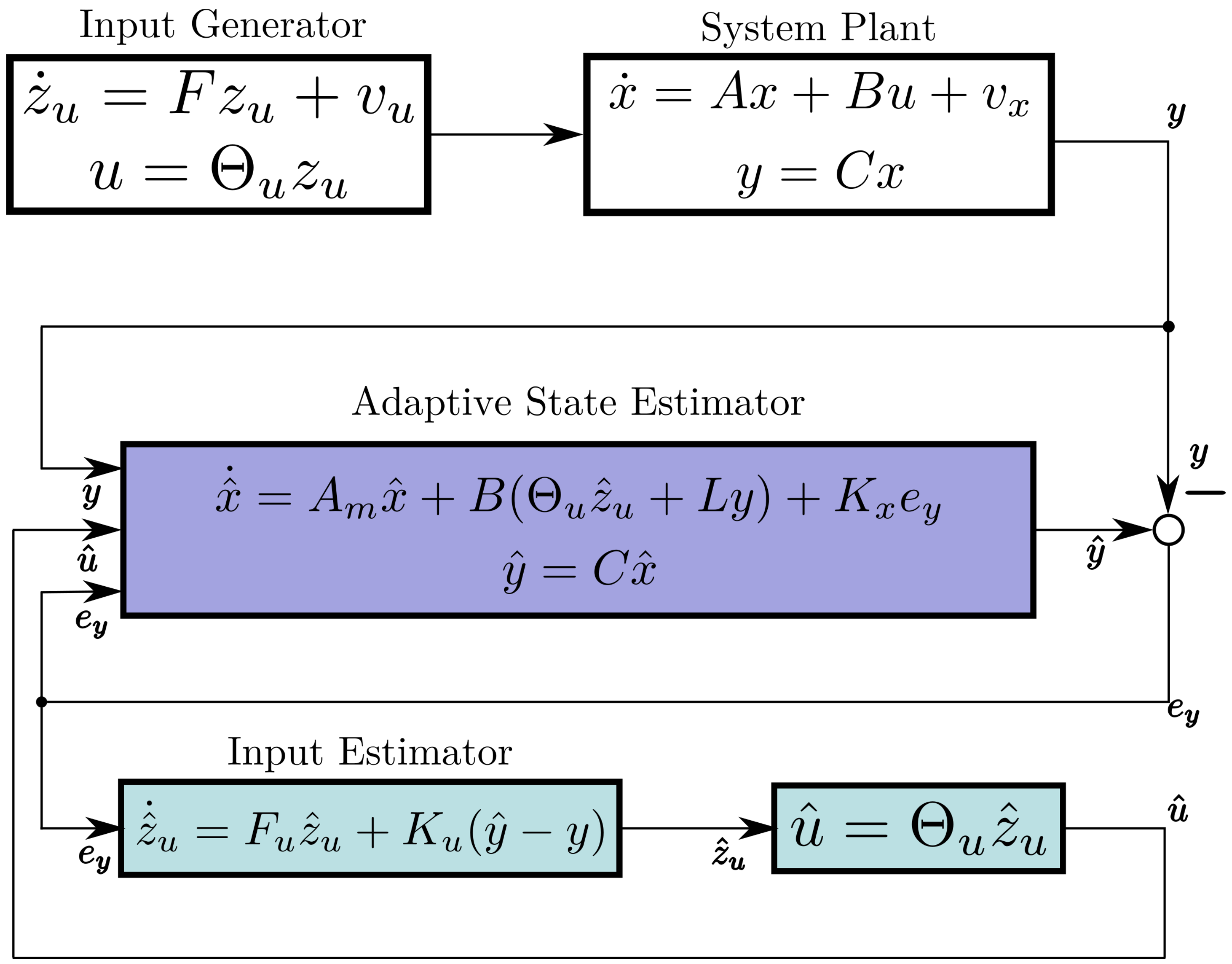
Persisten Inputs

- $\dot{z}_u = F_u z_u$
- $\hat{u} = \Theta_u z_u$
- $F_u = \begin{bmatrix} 0 & 1 & 0 \\ -\omega^2 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$



Adaptive Unknown Input Estimators

Architecture and estimator error



Recover A with adaptive scheme

$$A \equiv A_m + BL_* C$$

$$\dot{L} = -e_y y^* \gamma_e - \alpha L;\ \alpha > 0,\ \gamma_e > 0$$

Error dynamics

$$\dot{e} = (\bar{A} + \bar{K}\bar{C})e + \bar{B}w + v$$

$$\begin{bmatrix} \dot{e}_x \\ \dot{e}_z \end{bmatrix} = \left(\begin{bmatrix} A_m & B\Theta_u \\ 0 & F_u \end{bmatrix} + \begin{bmatrix} K_x \\ K_u \end{bmatrix} \begin{bmatrix} C & 0 \end{bmatrix} \right) \begin{bmatrix} e_x \\ e_z \end{bmatrix} + \begin{bmatrix} B \\ 0 \end{bmatrix} w + \begin{bmatrix} v_x \\ v_u \end{bmatrix}$$

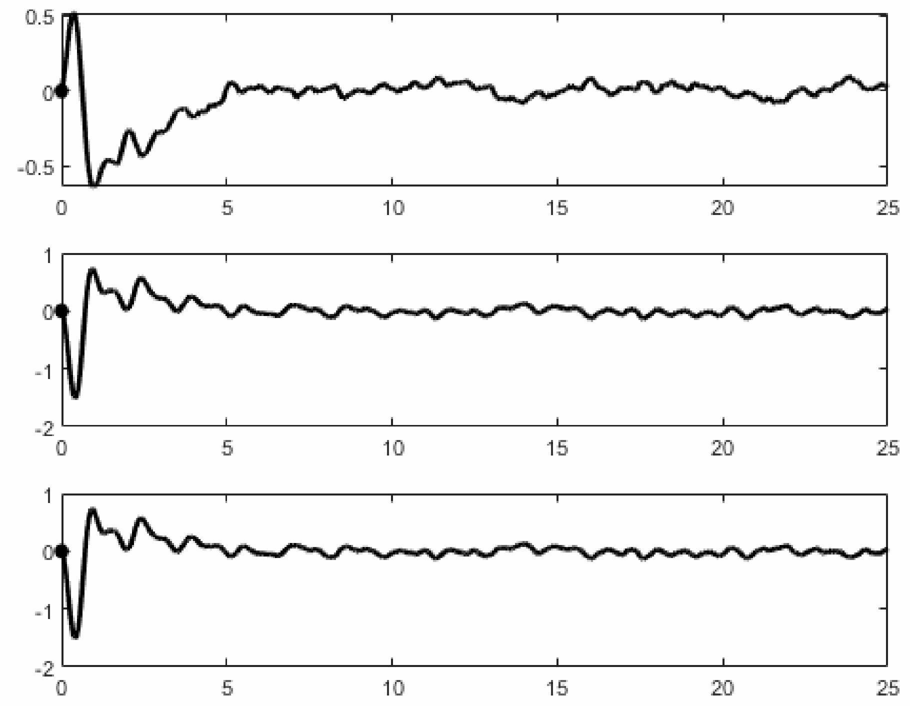
$$\begin{bmatrix} \dot{e}_x \\ \dot{e}_z \end{bmatrix} = \underbrace{\begin{bmatrix} A_m + K_x C & B\Theta_u \\ K_u C & F_u \end{bmatrix}}_{\bar{A}_c} \begin{bmatrix} e_x \\ e_z \end{bmatrix} + \begin{bmatrix} B \\ 0 \end{bmatrix} w + \begin{bmatrix} v_x \\ v_u \end{bmatrix}$$

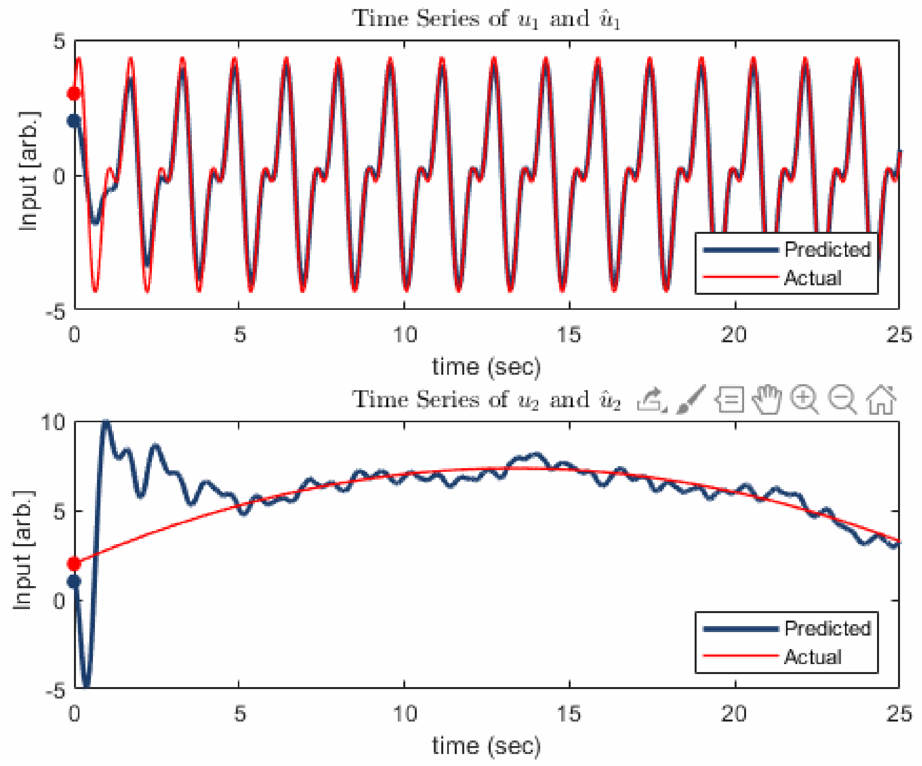
Adaptive Unknown Input Estimators

Architecture and estimator error

ASD plant dynamics
Bounded L_*, v, and γ_e
Error in state and input converges to an n-ball centered at zero

- $V(e, \Delta L) = \frac{1}{2} e^* \bar{P} e + \frac{1}{2} \mathrm{tr}(\Delta L {\gamma_e}^{-1} \Delta L^*)$
- $\lim_{t \to \infty} \sup ||e(t)|| \leq \frac{1+\sqrt{\lambda_{\max} \bar{P}}}{\alpha \sqrt{\lambda_{\min} \bar{P}}} M_v \equiv R^*$





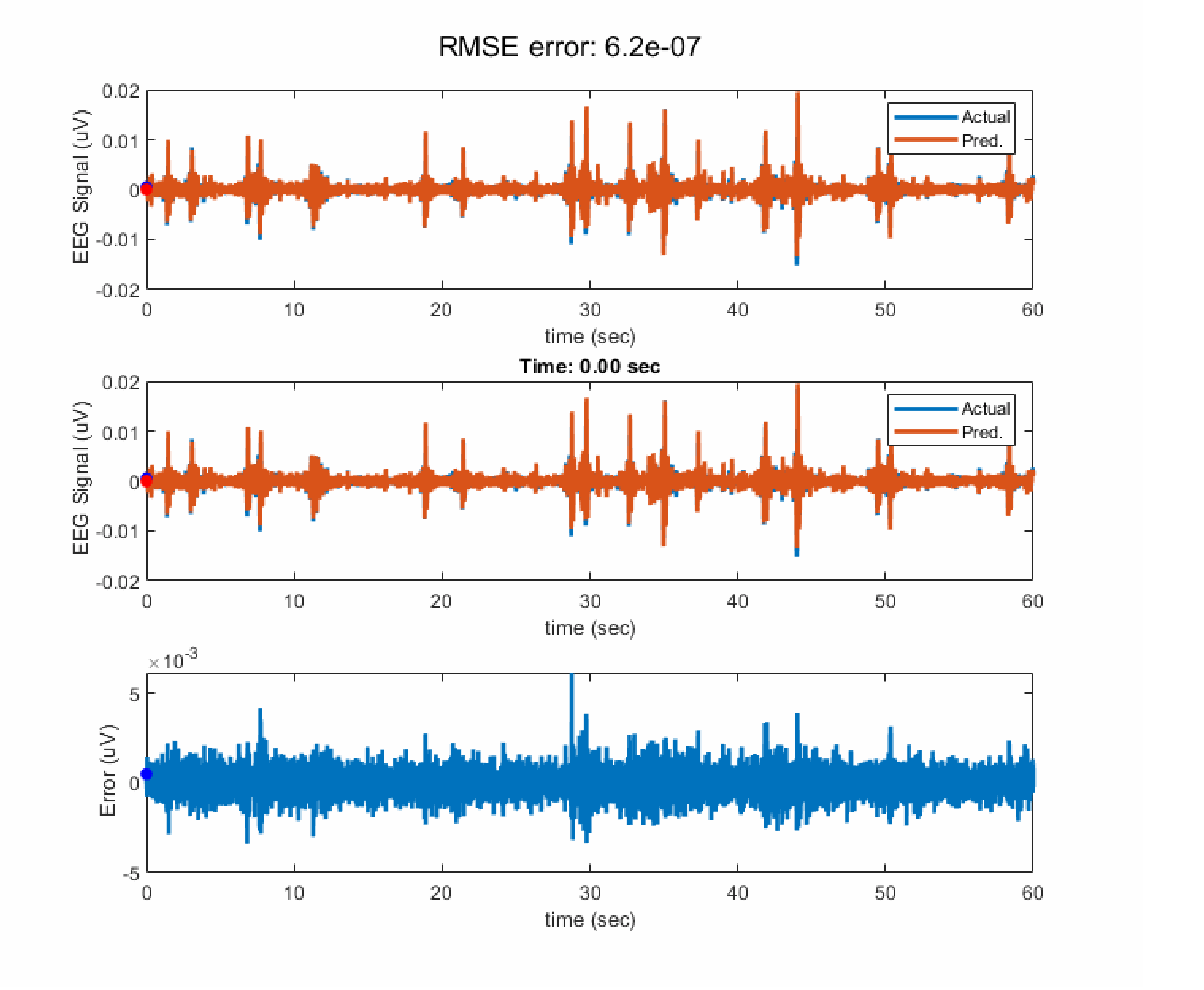
6. Reconstructing the Brain's Unknown Input

Recall: Solving the nonstationary problem

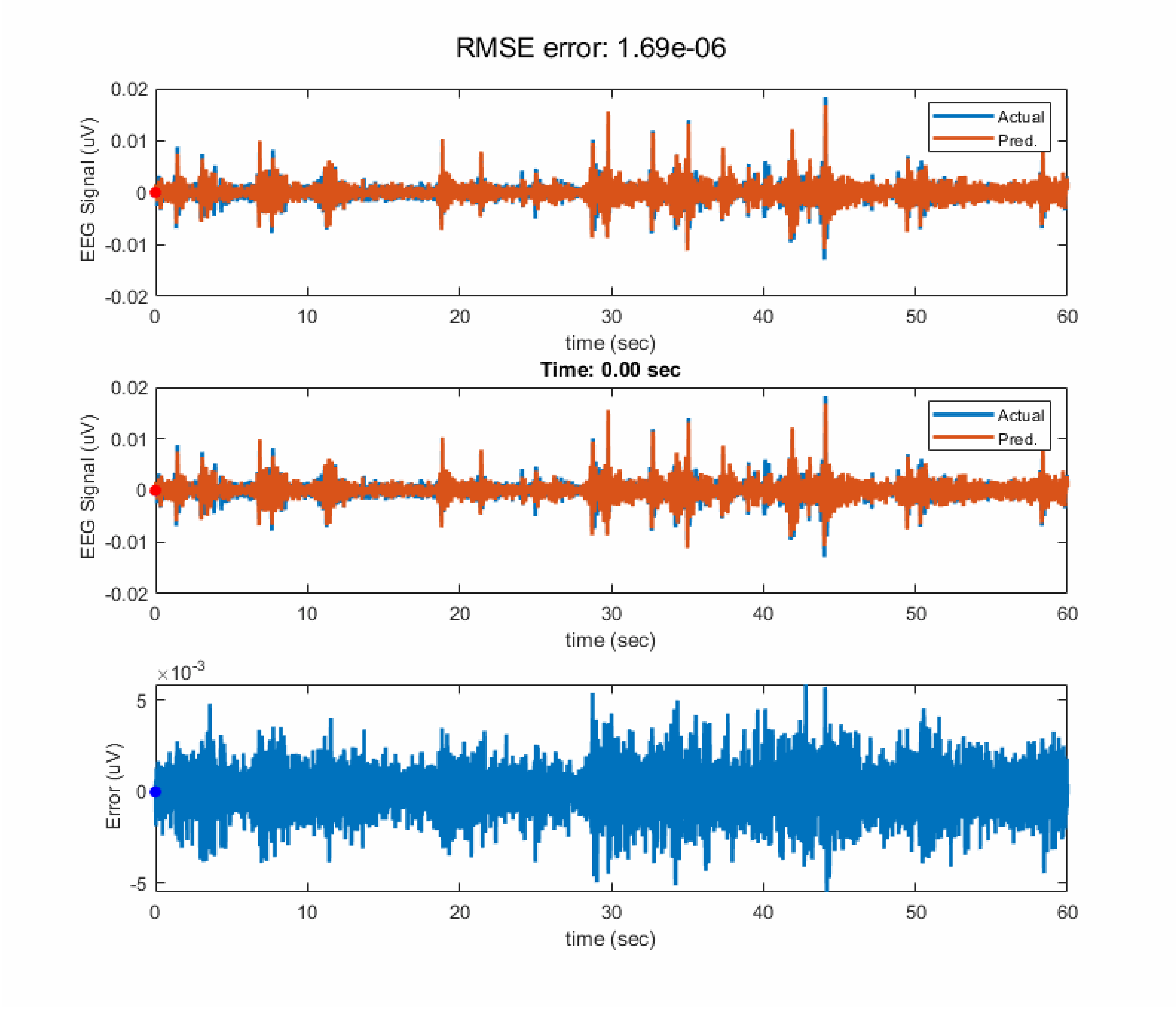
Reconstructing the Brain's Unknown Input

aUIO outperforms static modes

aUIO on unseen data



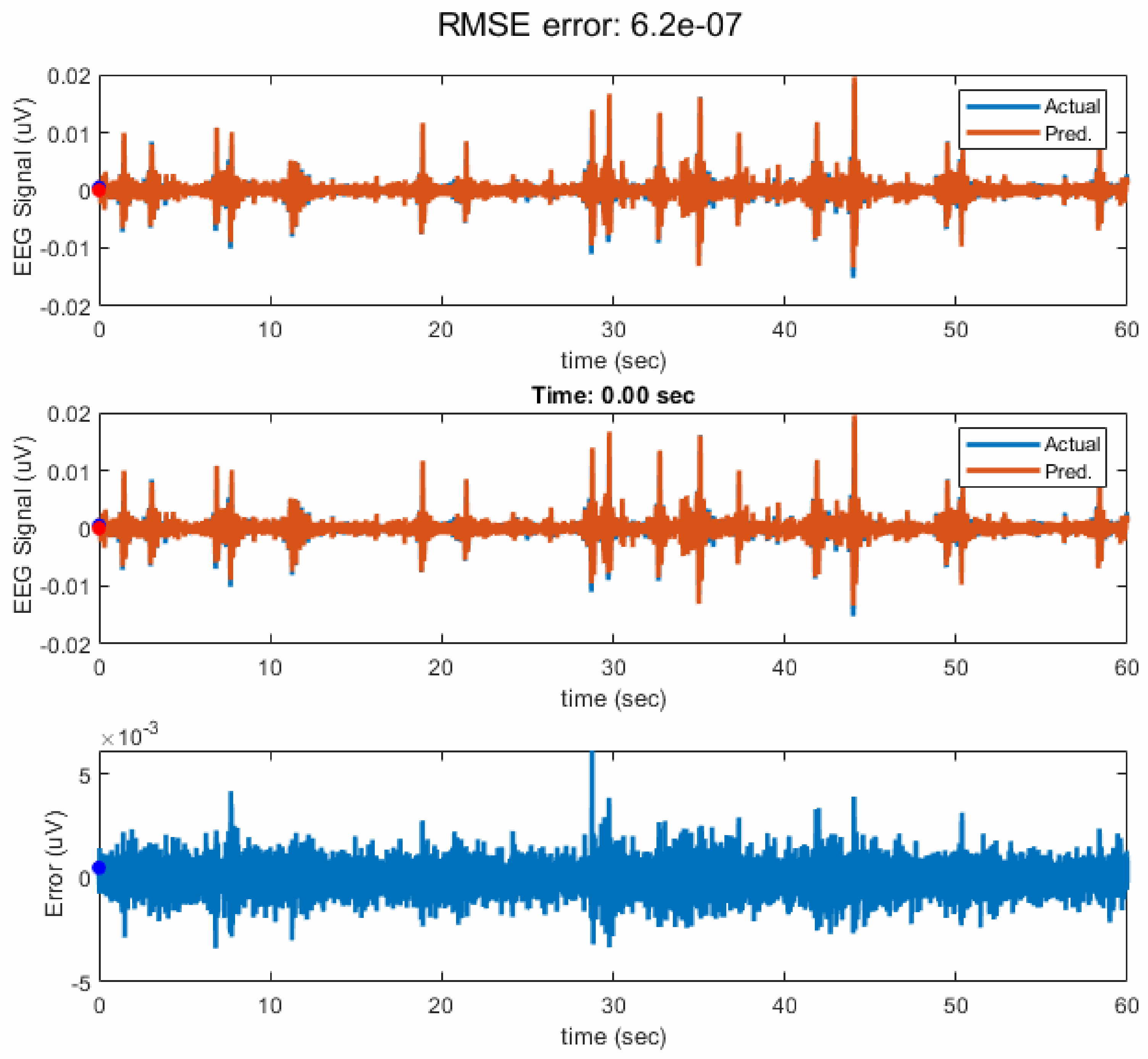
Weighted modes on seen data



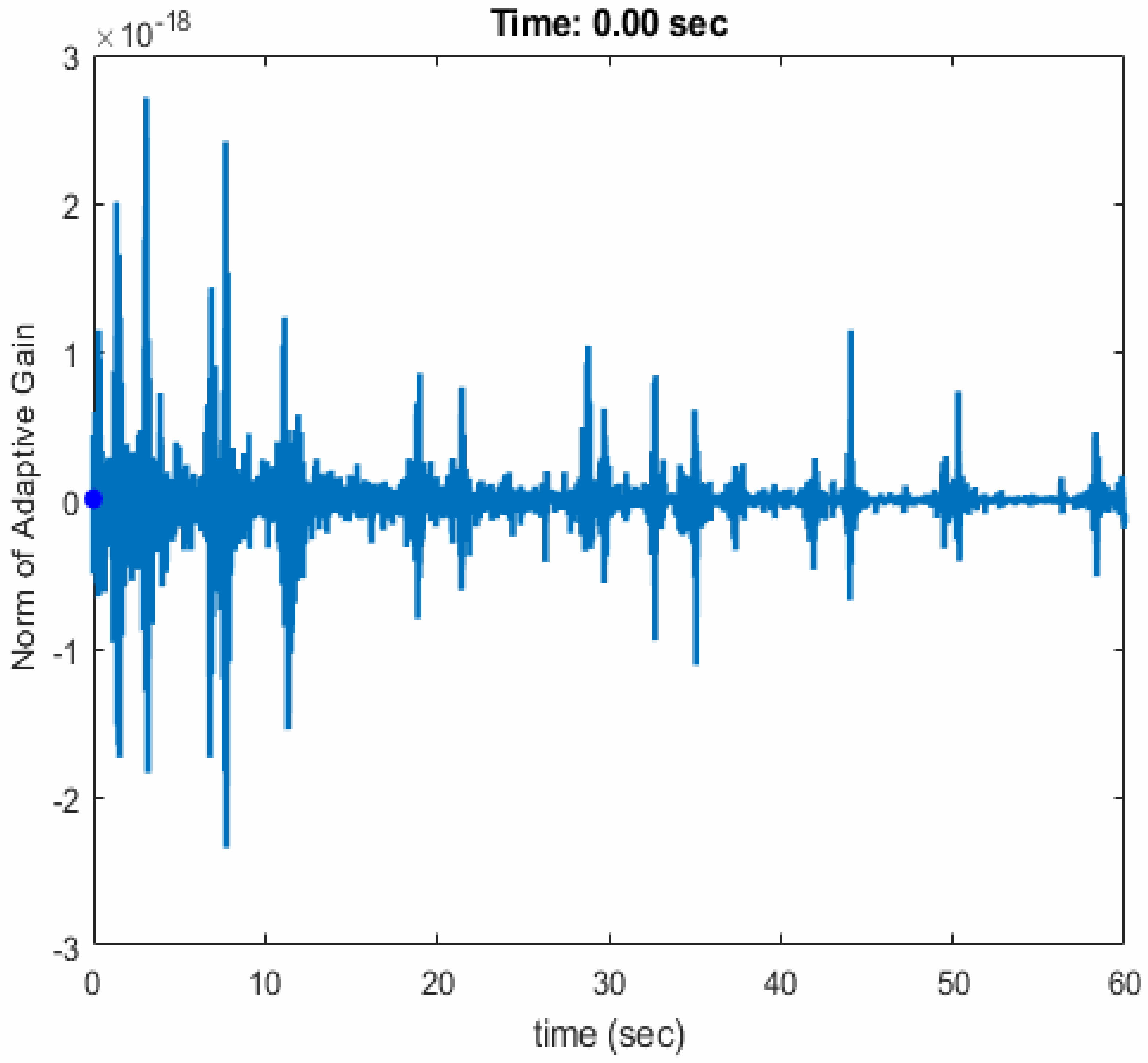
Reconstructing the Brain's Unknown Input

aUIO critically updates model as needed

aUIO on unseen data



Adaptive gain matrix 2-norm



Reconstructing the Brain’s Unknown Input

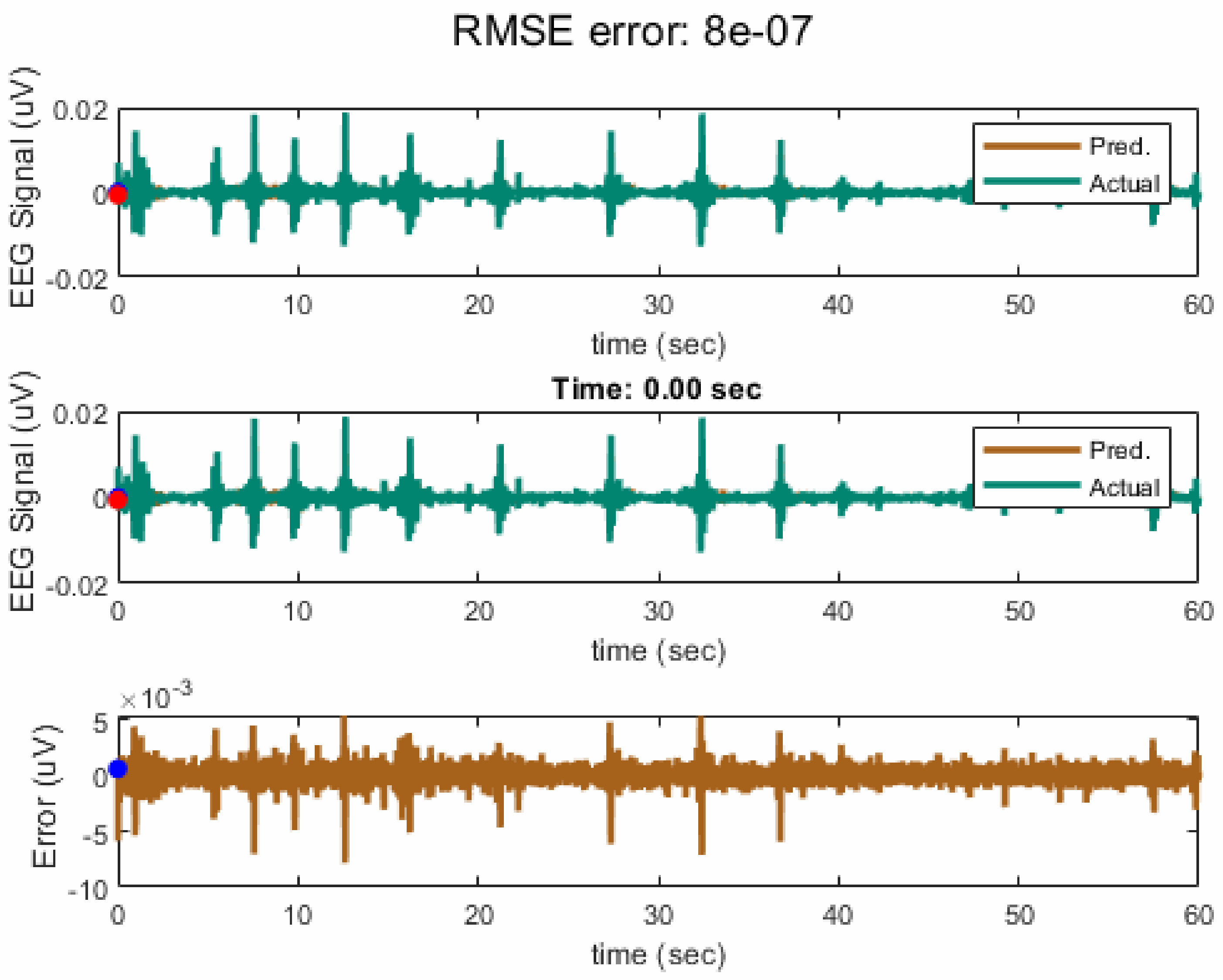
Modeling details

- Unknown input acts evenly over spatial domain
- F_u generates sine-cosine basis
- Static gains per LQR

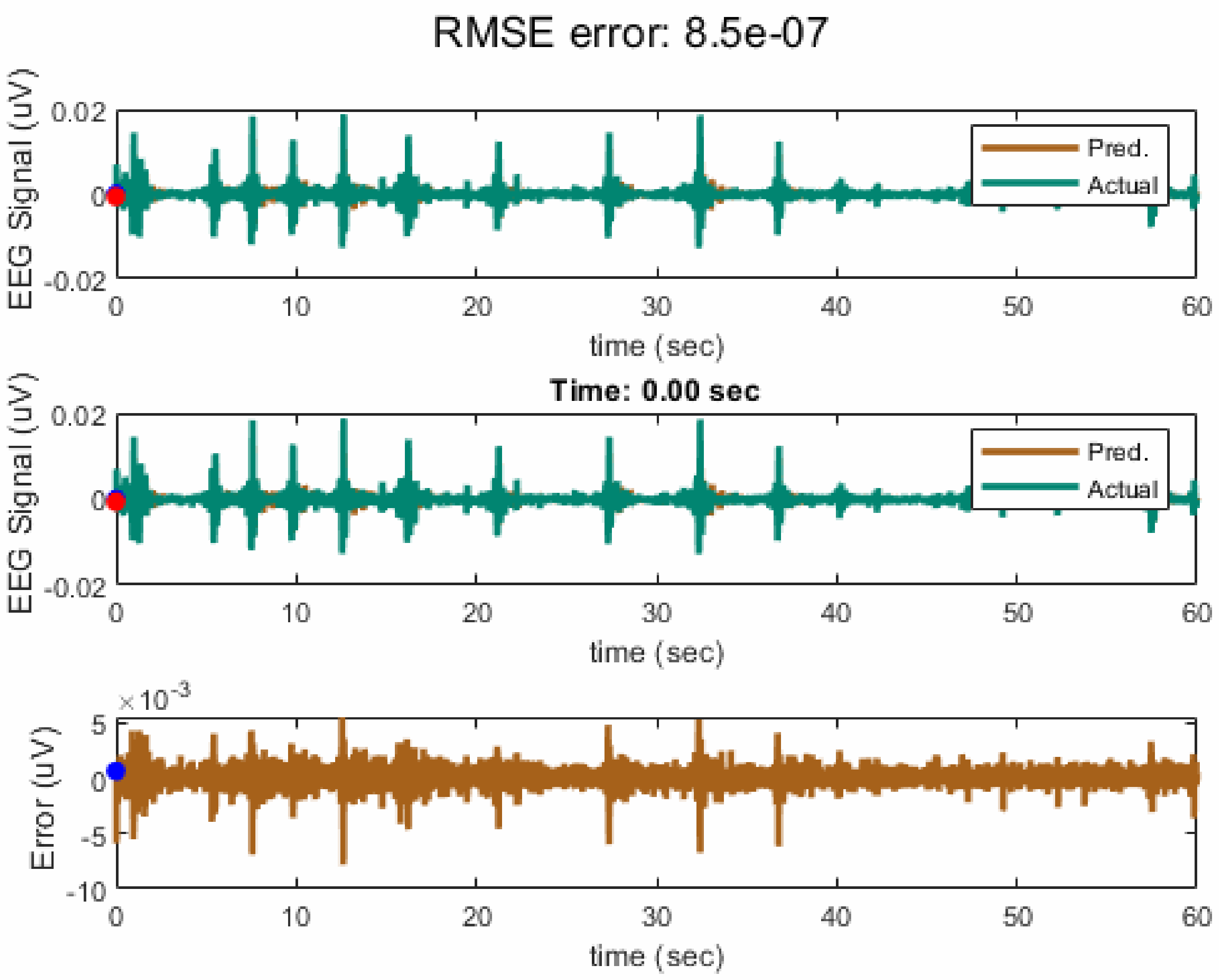
Reconstructing the Brain's Unknown Input

aUIO is tolerant to parametric uncertainty in modes

aUIO on unseen data

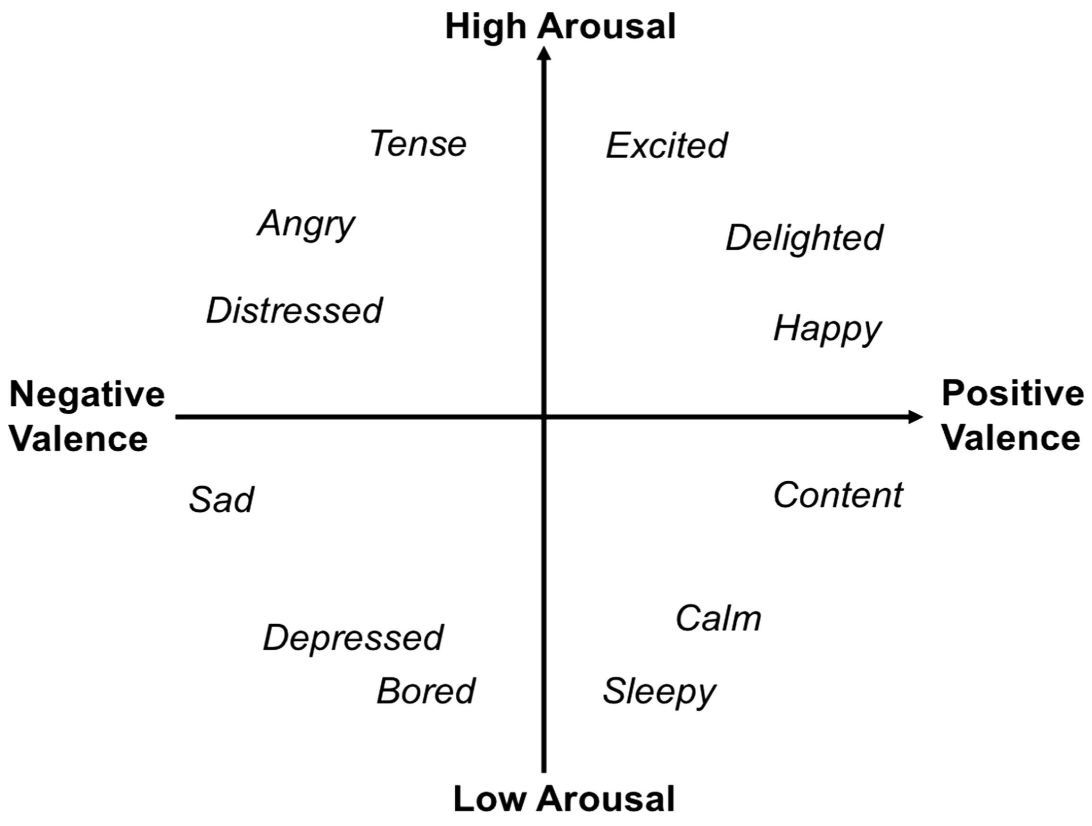


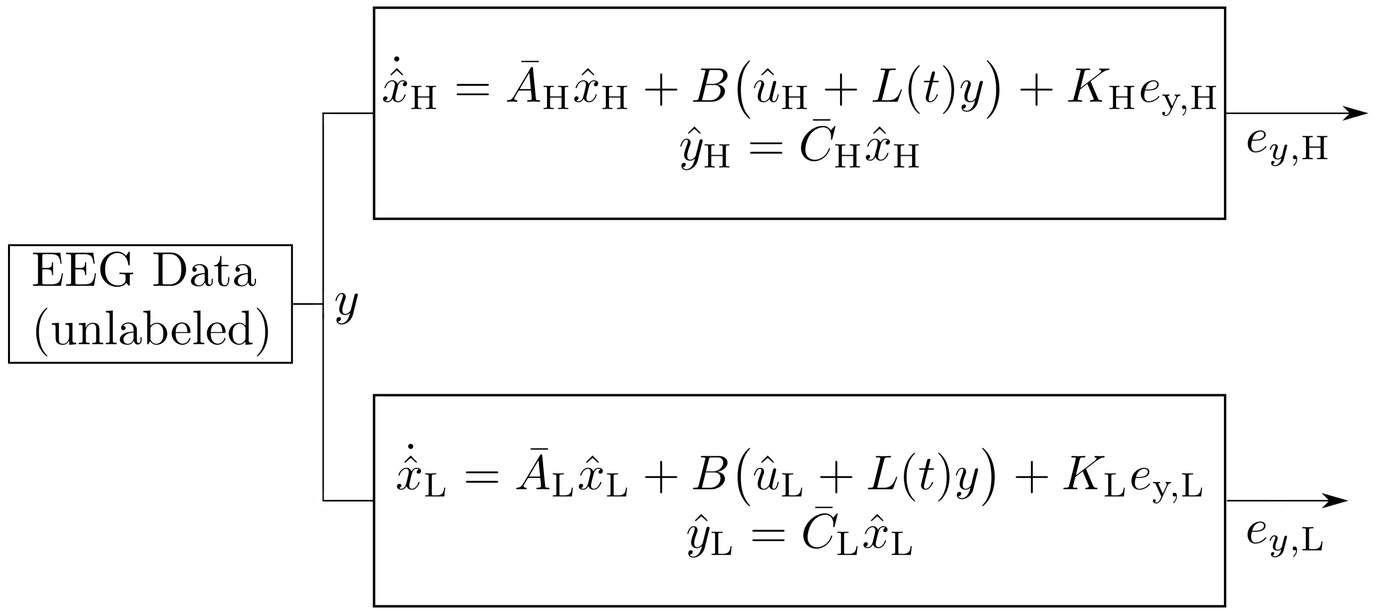
aUIO with wrong A_m



Reconstructing the Brain's Unknown Input

Classification via estimation

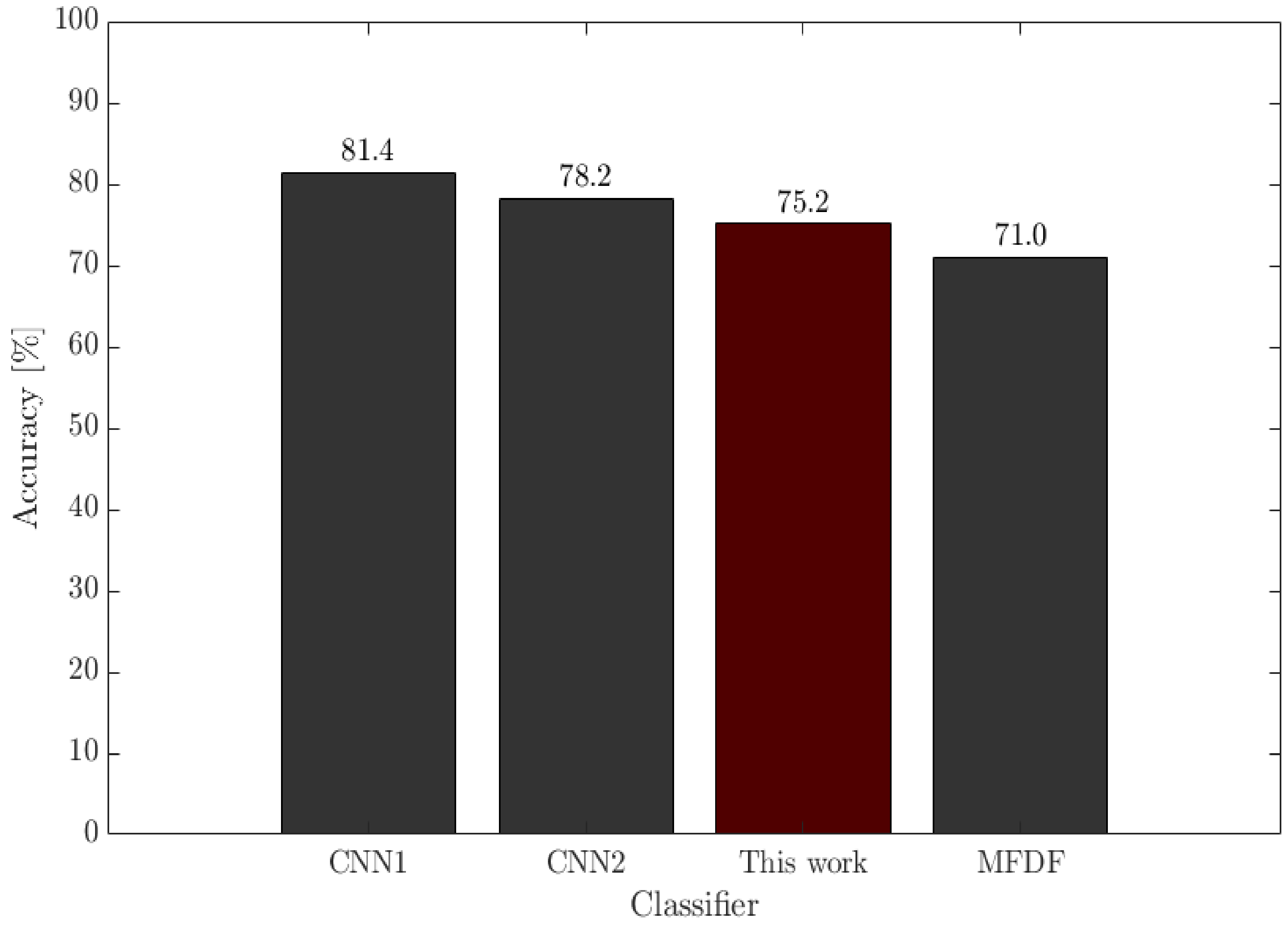




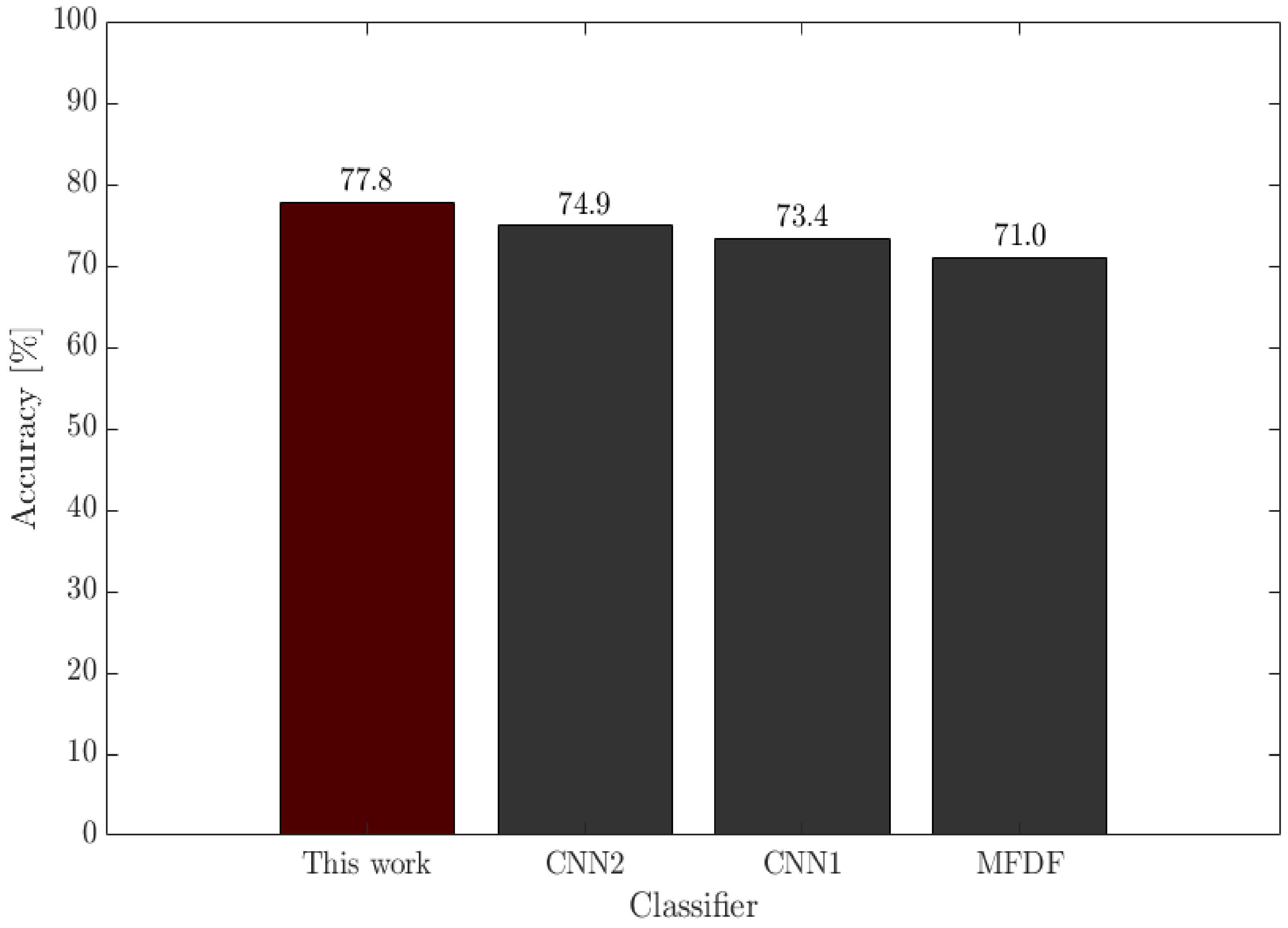
Reconstructing the Brain's Unknown Input

Classification via estimation

Valence Classification



Arousal Classification



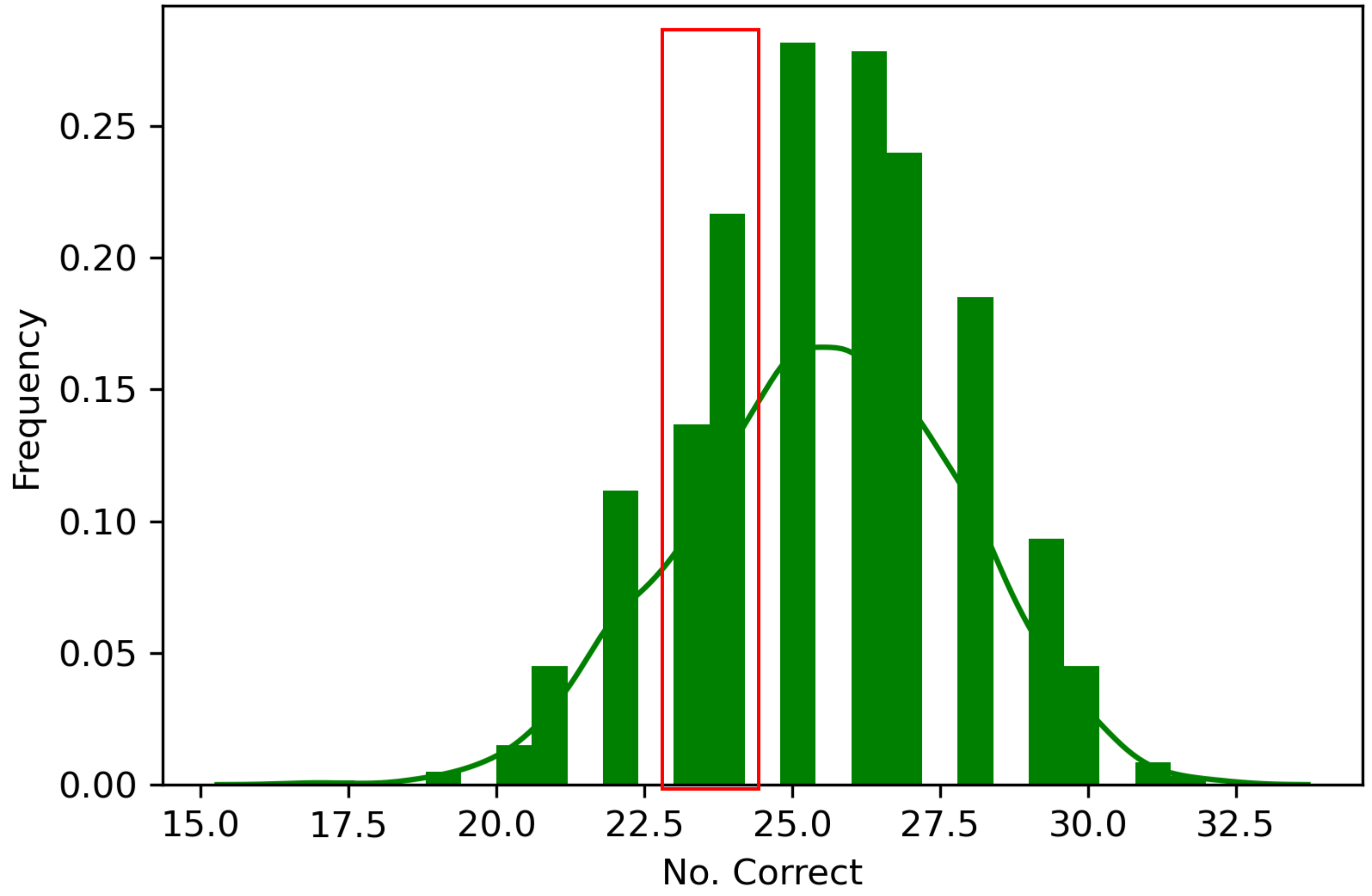
CNN1, CNN2, MFDF

Reconstructing the Brain's Unknown Input

Classification validation

Task	aUIO Acc. [%]	PSD CNN Acc. [%]
DEAP Valence	77.8	68.1
DEAP Arousal	75.2	63.8
Like/Dislike	79.4	67.3

Static gain grid search



7. Conclusions

Summary

- Modern, sys-id techniques work on biomarker data
- Modal representation aids interpreation and analysis
- Complete body of UIO work
- Online estimation of nonlinear brain wave dynamics

Future work

- Multiple data types
- Improved analysis and classification
- Probablistic considerations

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- Zaryab Shahid
- Lise Ochej
- Kevin Fuentes

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- Sandra Havens
- Rebecca Simon
- Prof. Joanna Tsenn
- Kaustubh Mahesh Tangsali
- Briana Holton
- Bryton Praslicka
- Robert Trépanier
- Harold Gamarro

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Highly organized research is guaranteed to produce nothing new.