A Modal Approach to the Dynamics of Human Affect

T. Griffith

Preliminary Examination

May 20, 2021

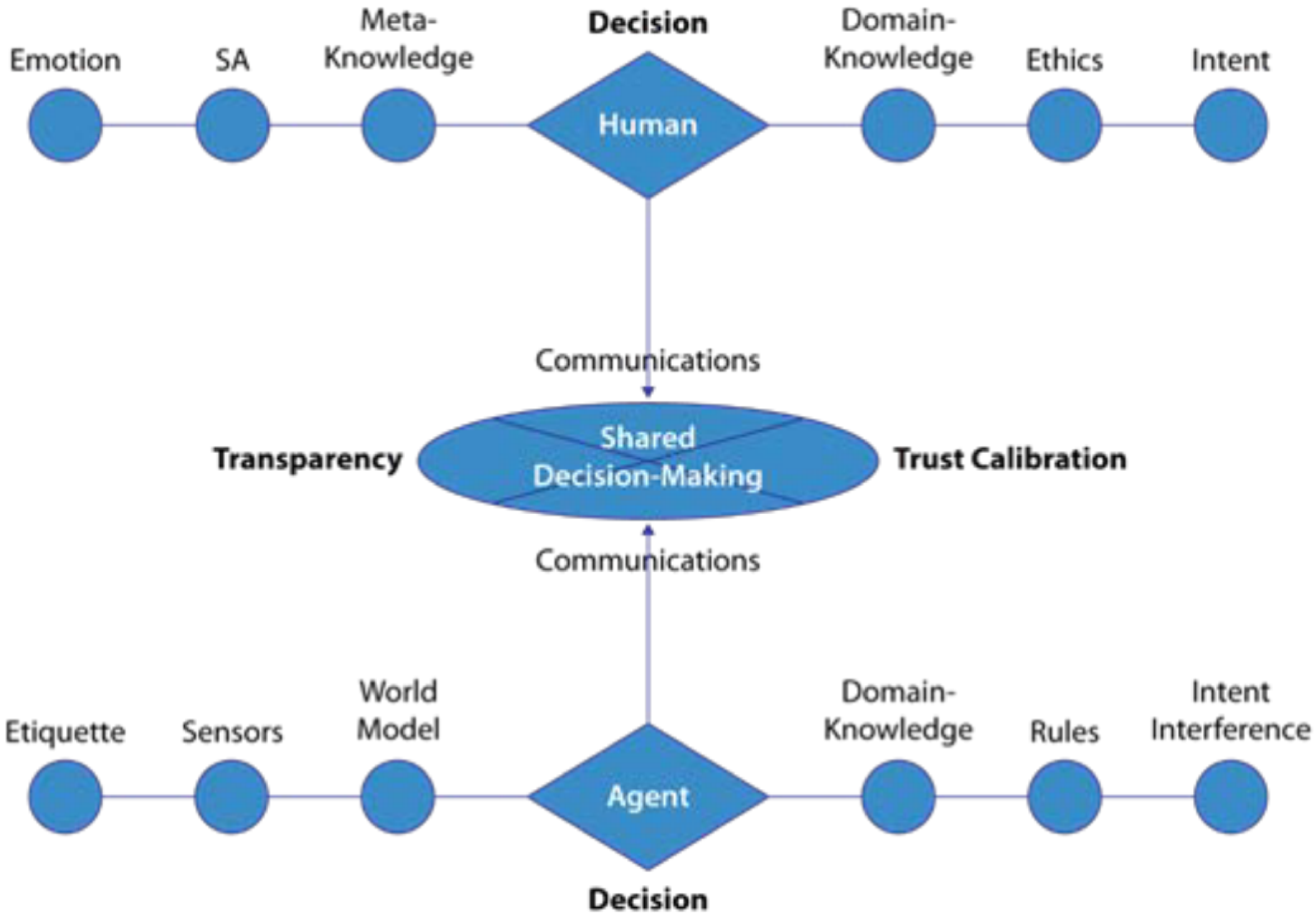
1. Motivation
2. Approach
3. Timeline

1. Motivation

Robots that work with humans are increasingly prevalent

Spencer Lowell, Wired, 2021
Army, 2009

Shared flow of information is implied



Barnes, Michael J., Jessie Y. Chen, and Susan Hill. Humans and autonomy: Implications of shared decision making for military operations. US Army Research Laboratory Aberdeen Proving Ground United States, 2017.

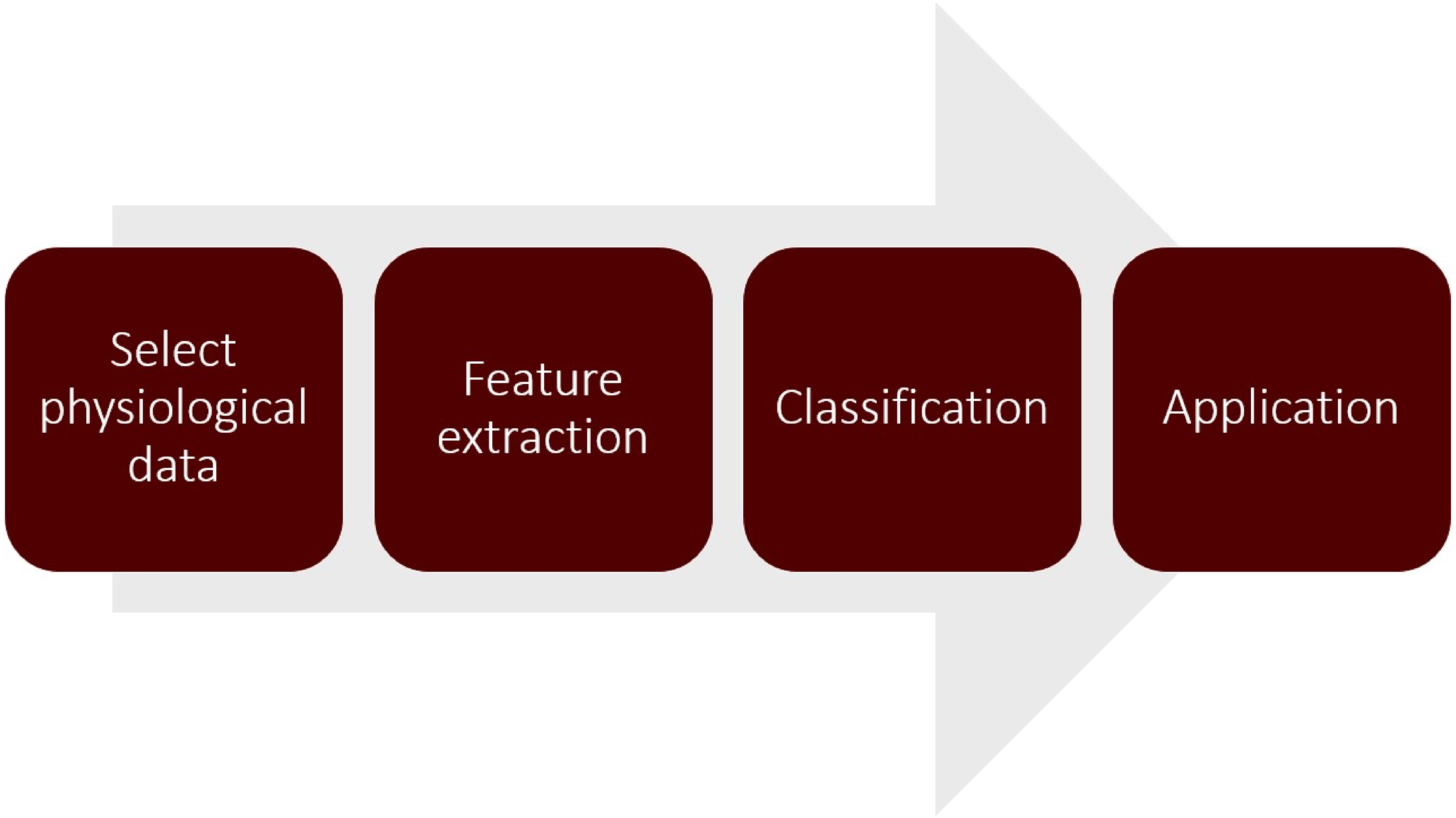
Not just performance

- Automation conundrum
- When SA is lost, bad things happen

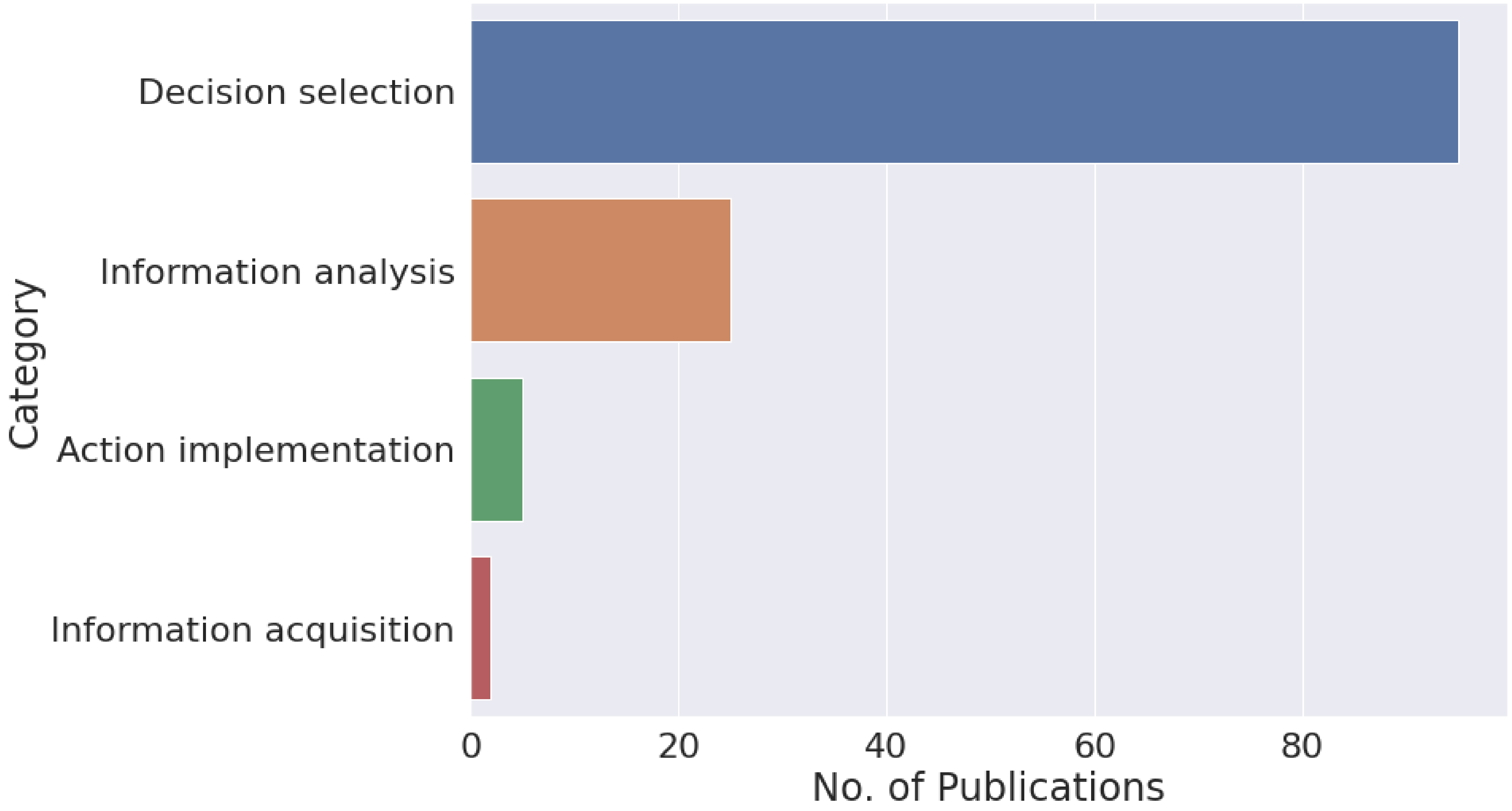
Need descriptions of human cognition and decision making as it is relevant to the **dynamics** of human-robot interaction.

- Rigorous
- Transparent
- Non-invasive
- Physiological

How is it done now?

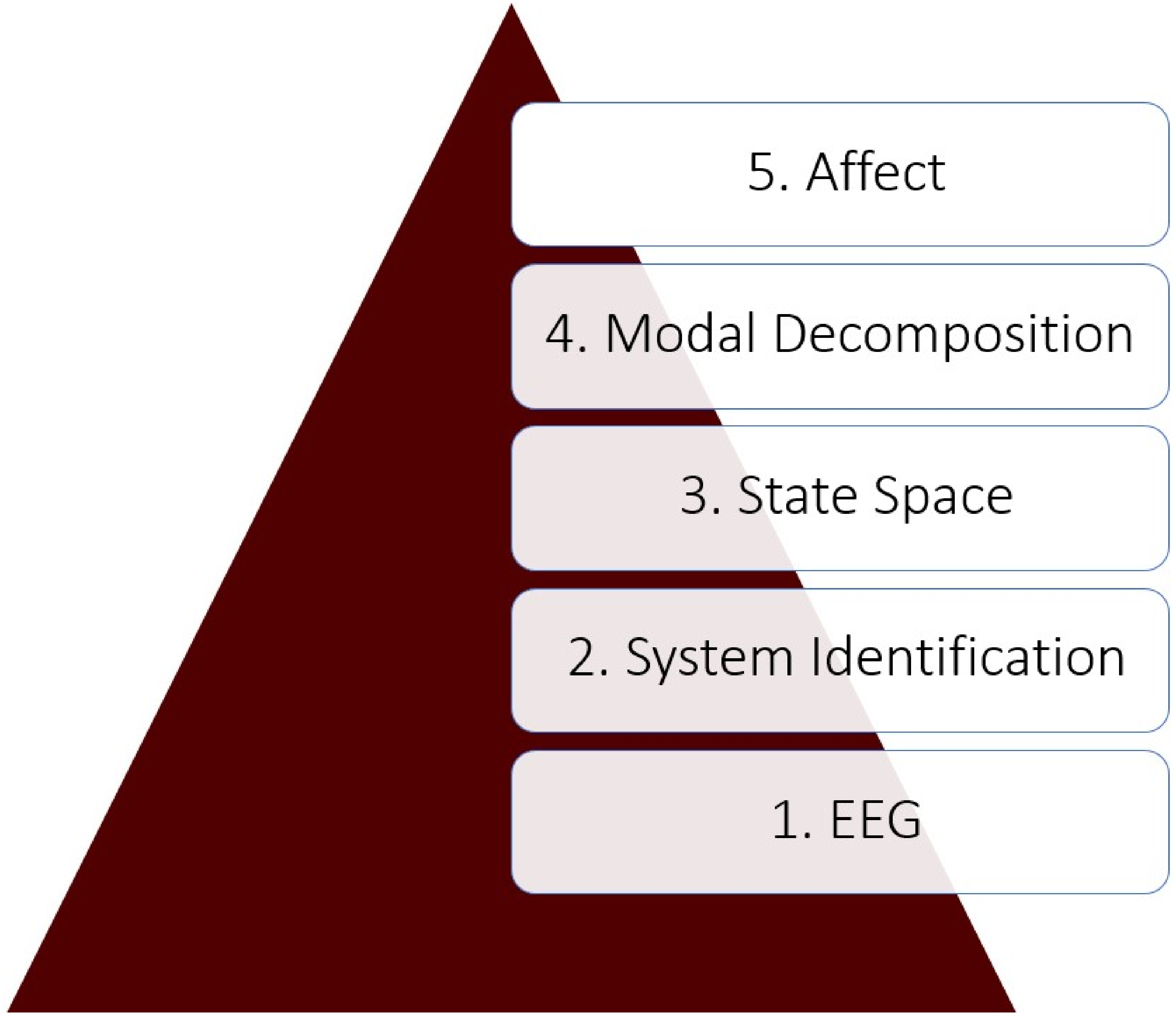


How is it done now?



2. Approach

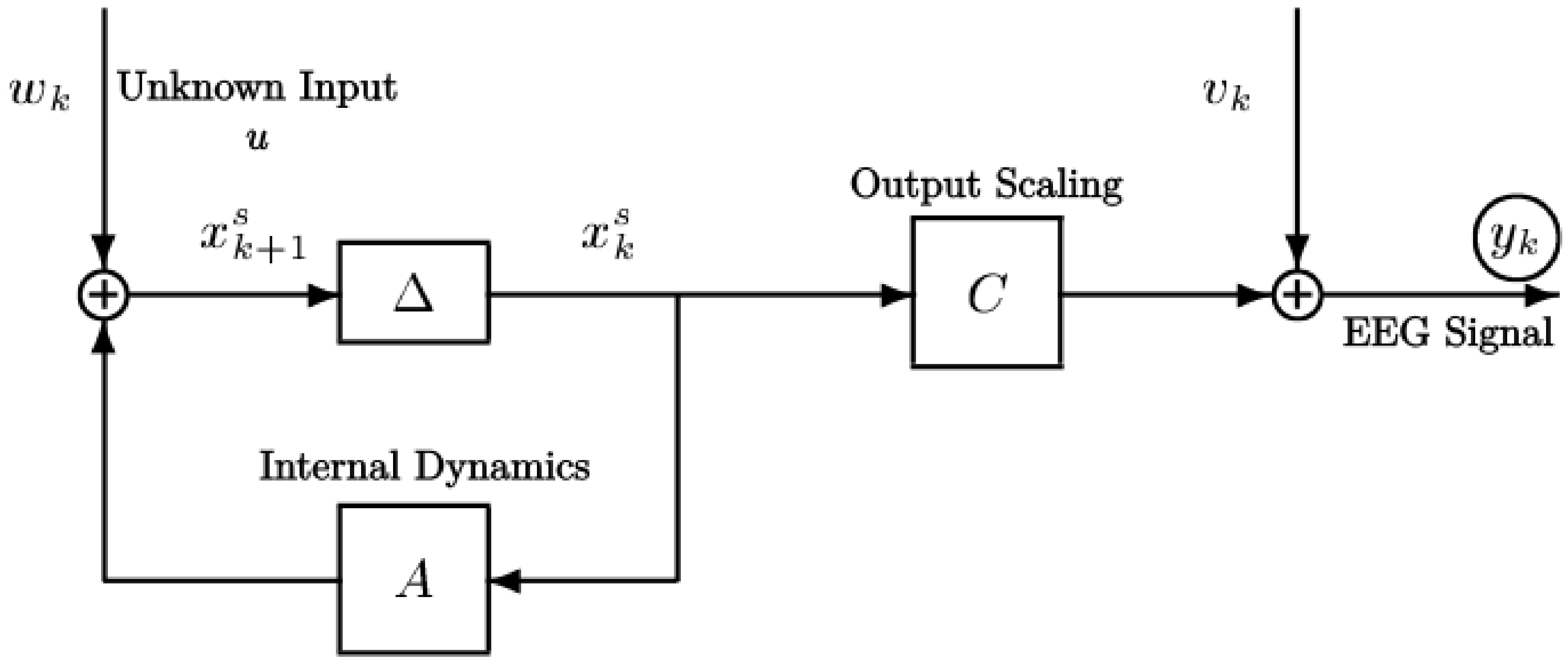
Key Components of the Approach



1. EEG is the measure of choice

- Lots of existing knowledge
- Widely available
- Implementation

2. System Identification



3. State space

$$x(k+1) = Ax(k)$$

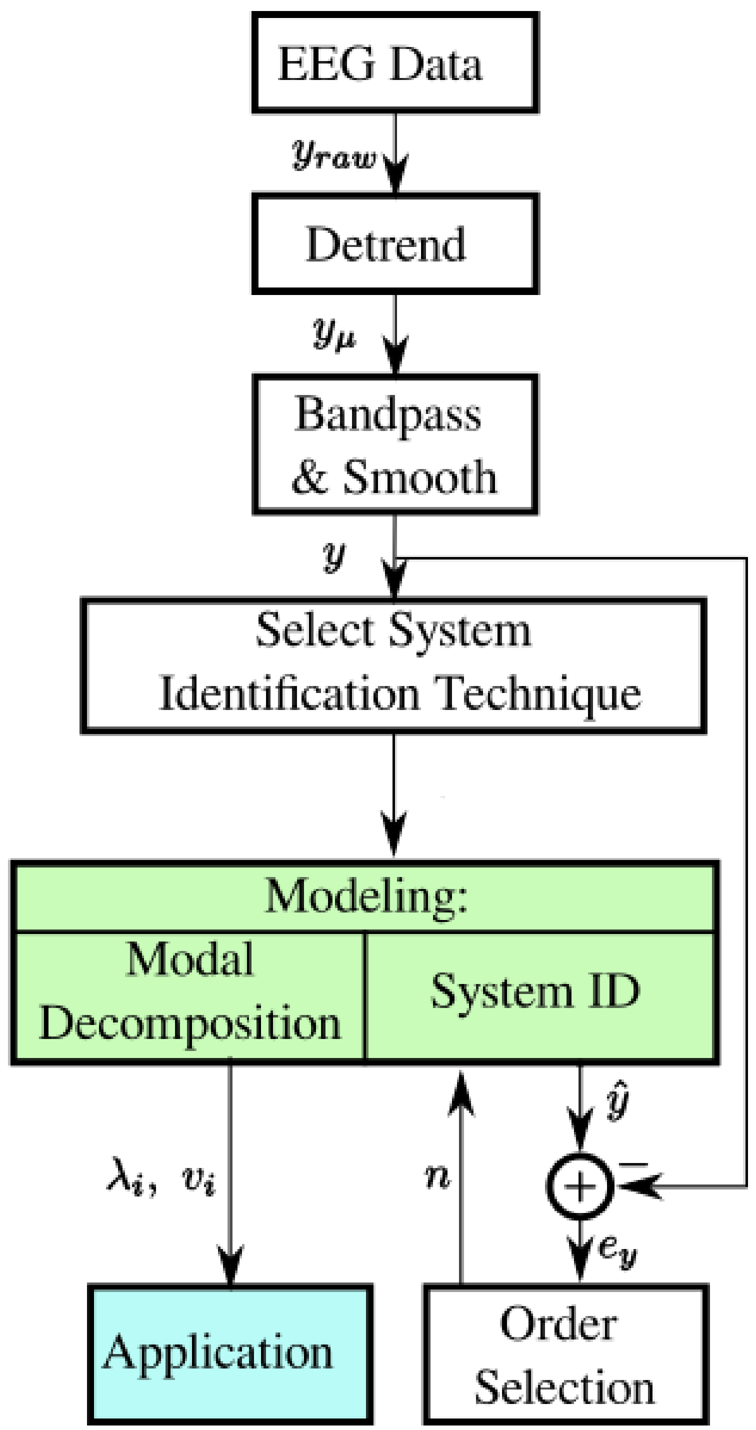
$$y(k) = Cx(k)$$

4. Modal decomposition

$$A = W\Lambda V$$

$$A = \begin{bmatrix} w_1 & w_2 & \dots & w_n \end{bmatrix} \begin{bmatrix} \lambda_1 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \lambda_n \end{bmatrix} \begin{bmatrix} v_1^T \\ v_2^T \\ \vdots \\ v_n^T \end{bmatrix}$$

Modeling Overview



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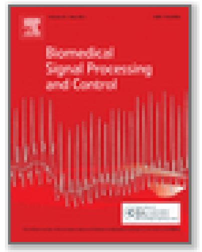

System identification methods for dynamic models of brain activity

Tristan D. Griffith, James E. Hubbard Jr.

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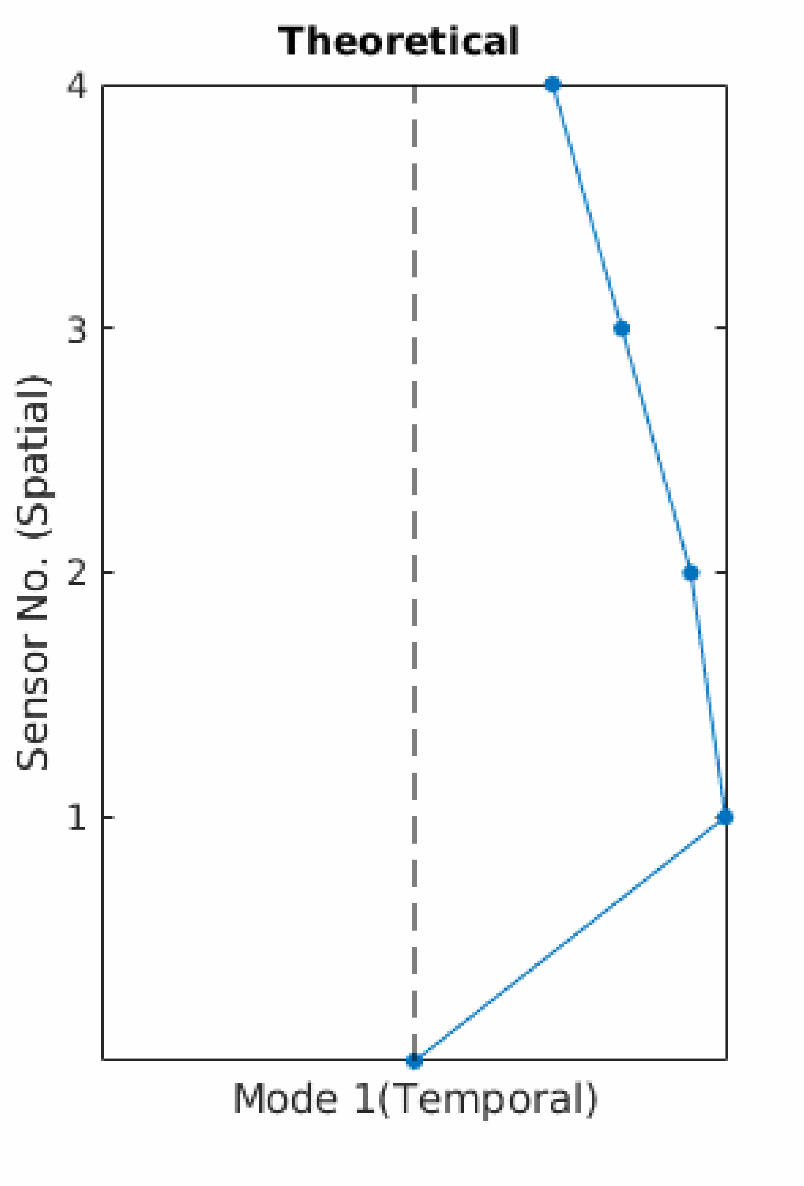
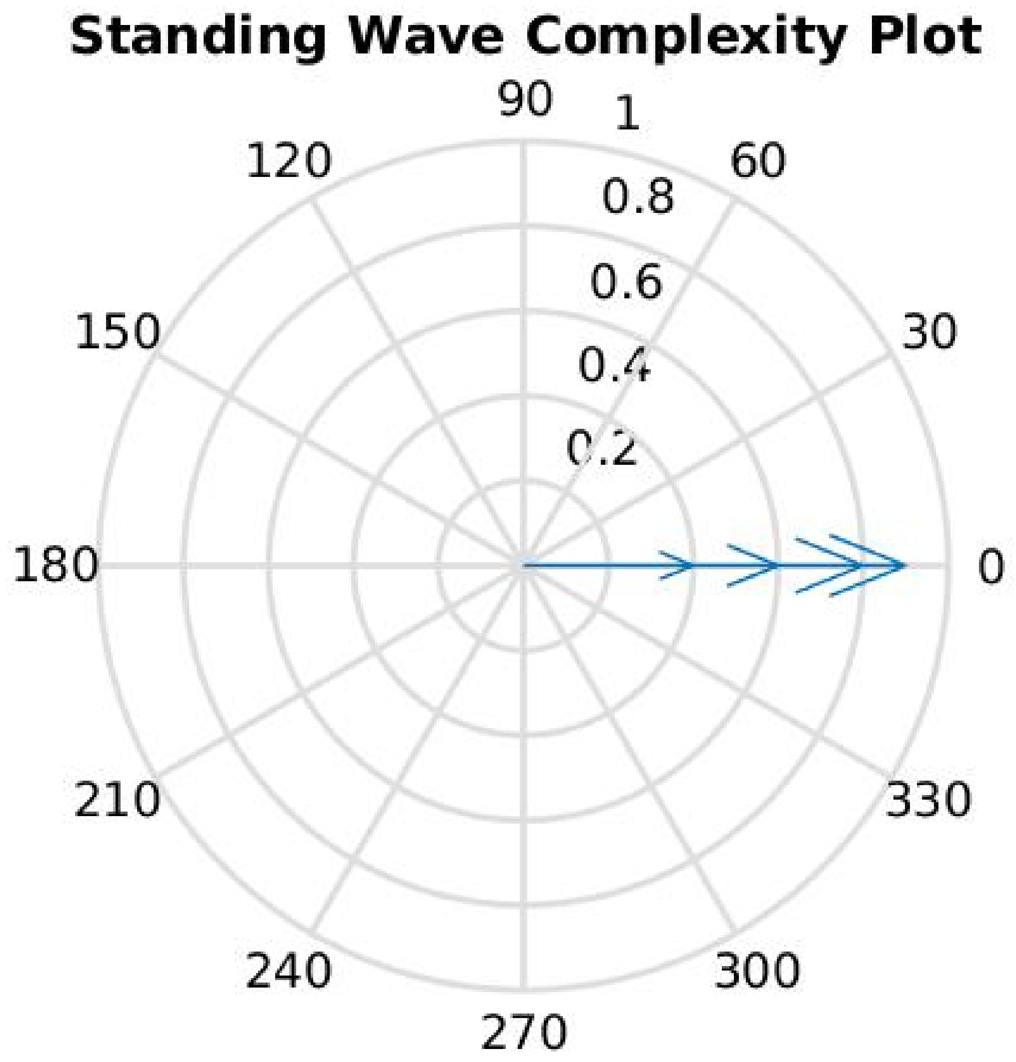
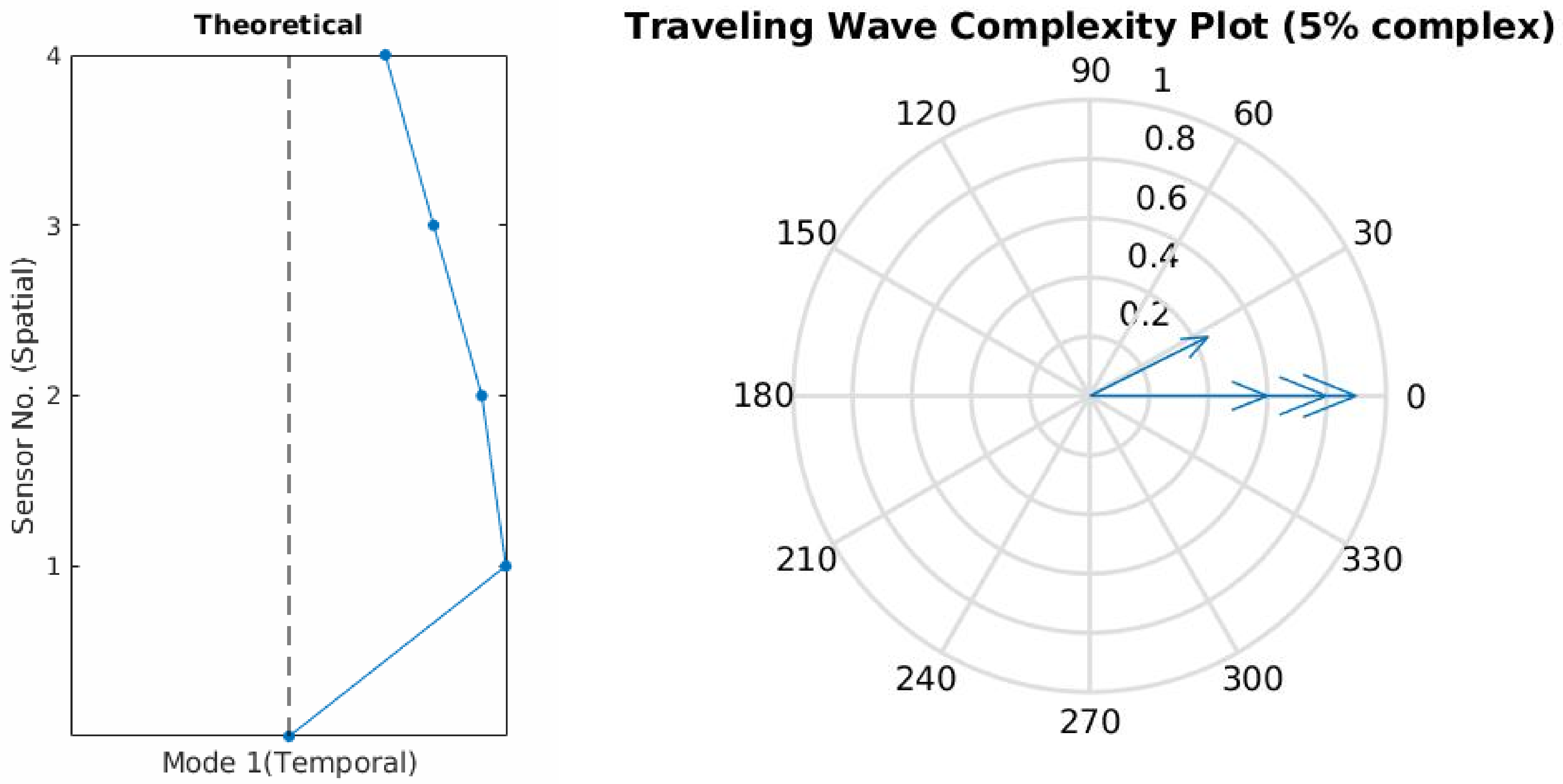
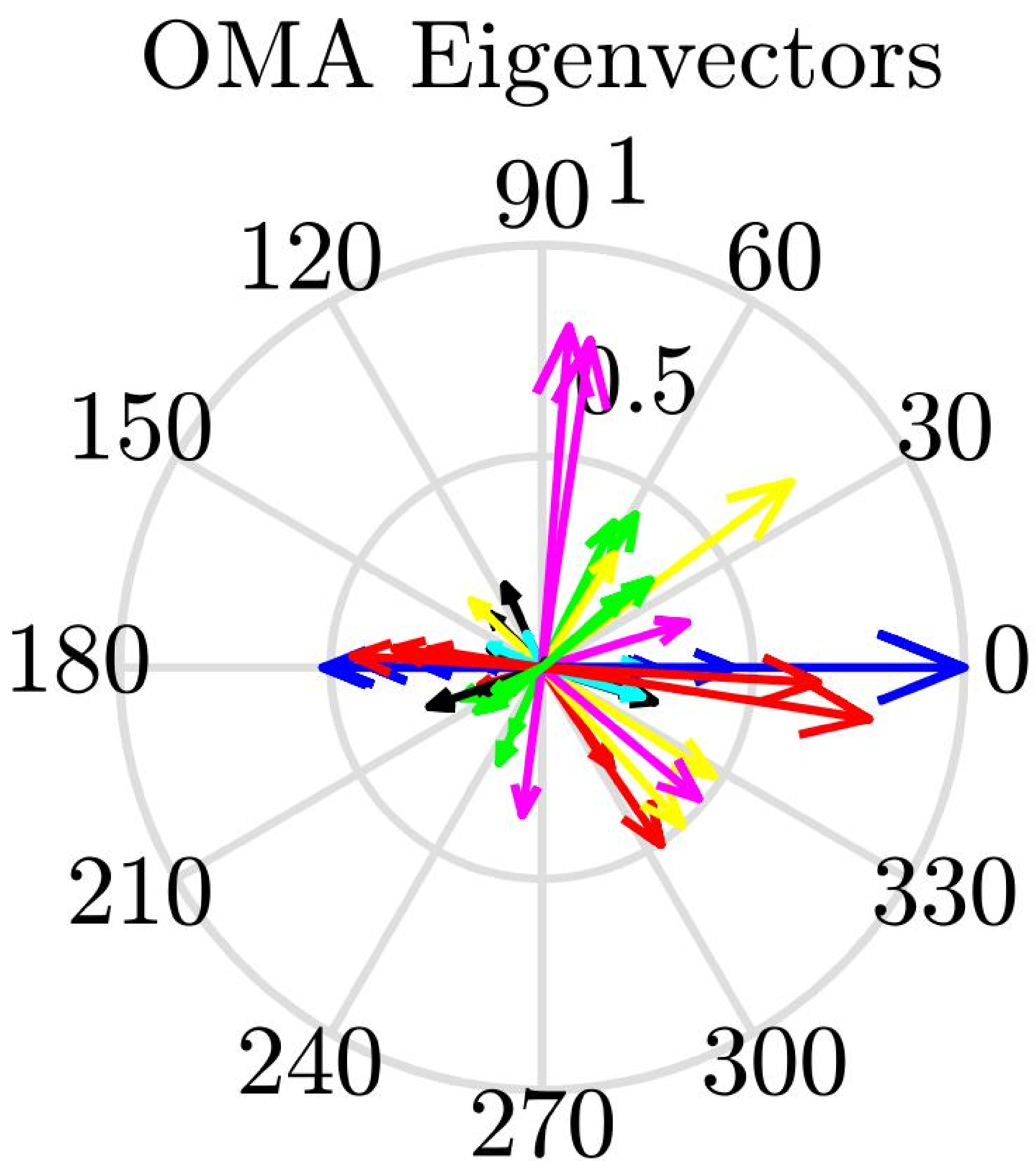
Brain Modes are Traveling and Standing

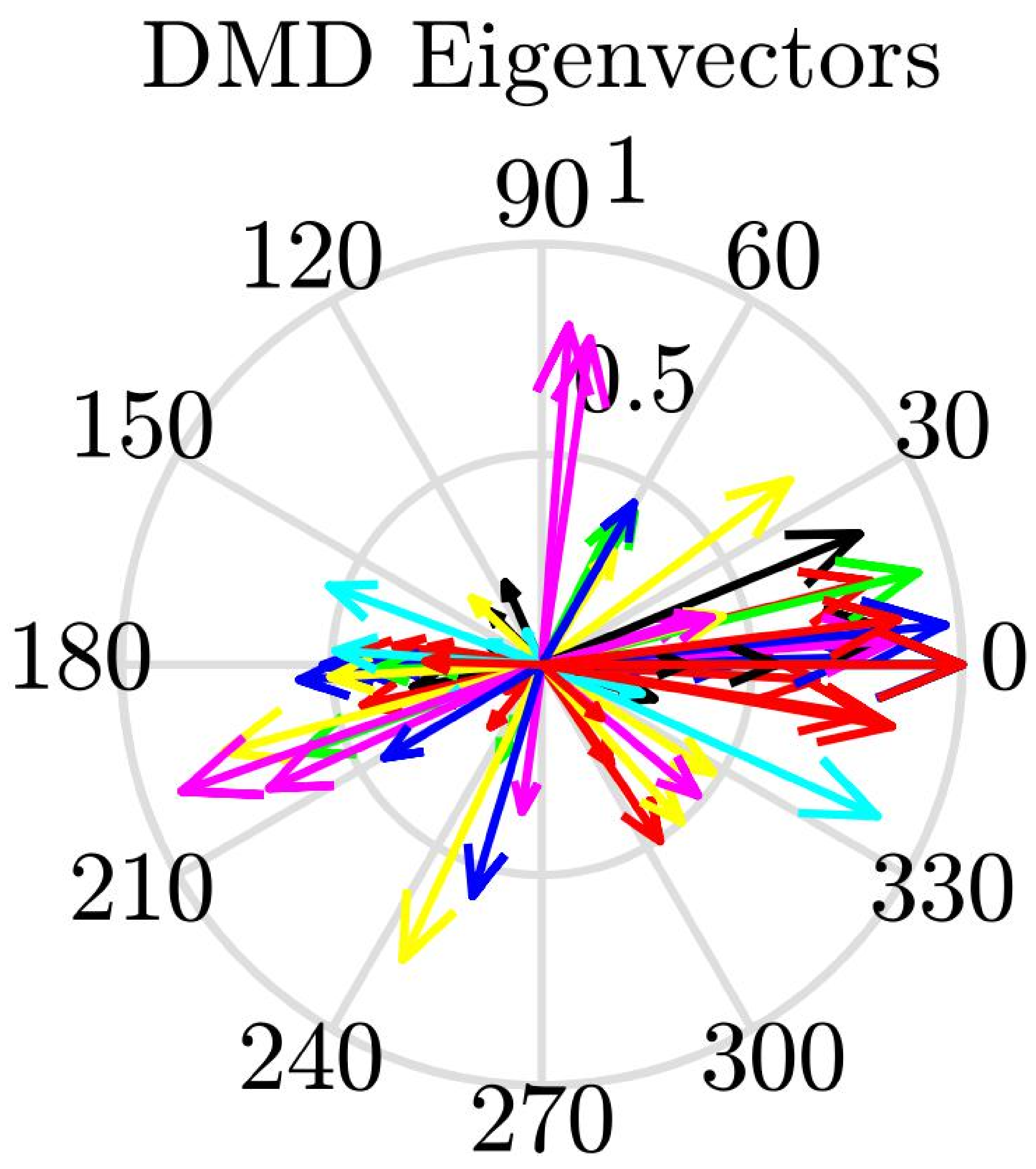





Theoretical
Sensor No. (Spatial)
Mode 1(Temporal)
4
3
2
1
Traveling Wave Complexity Plot (5% complex)
90
120
60
150
30
180
0
210
330
240
300
270
1
0.8
0.6
0.4
0.2

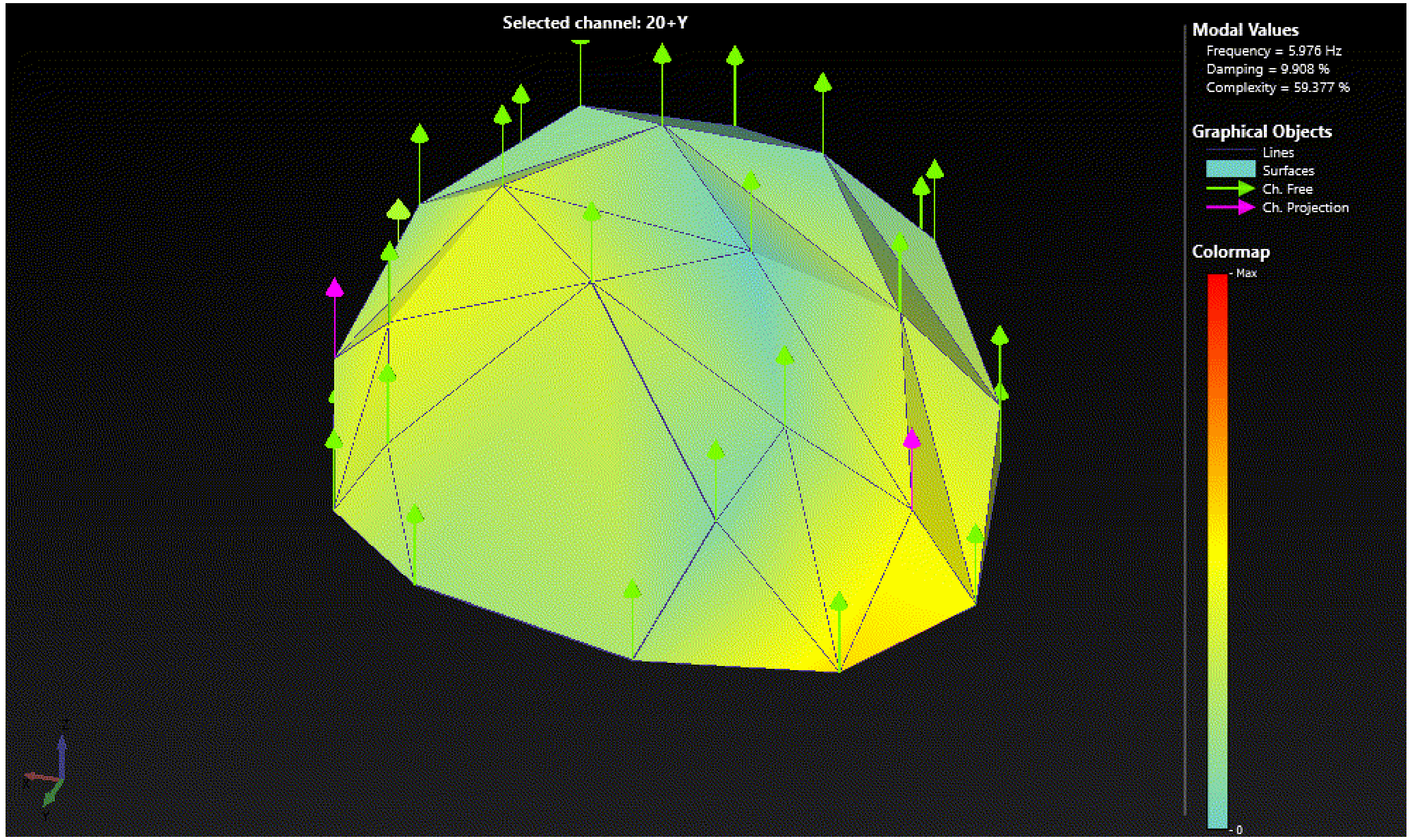
- Comparing normalized complexity plots from two output only decompositions

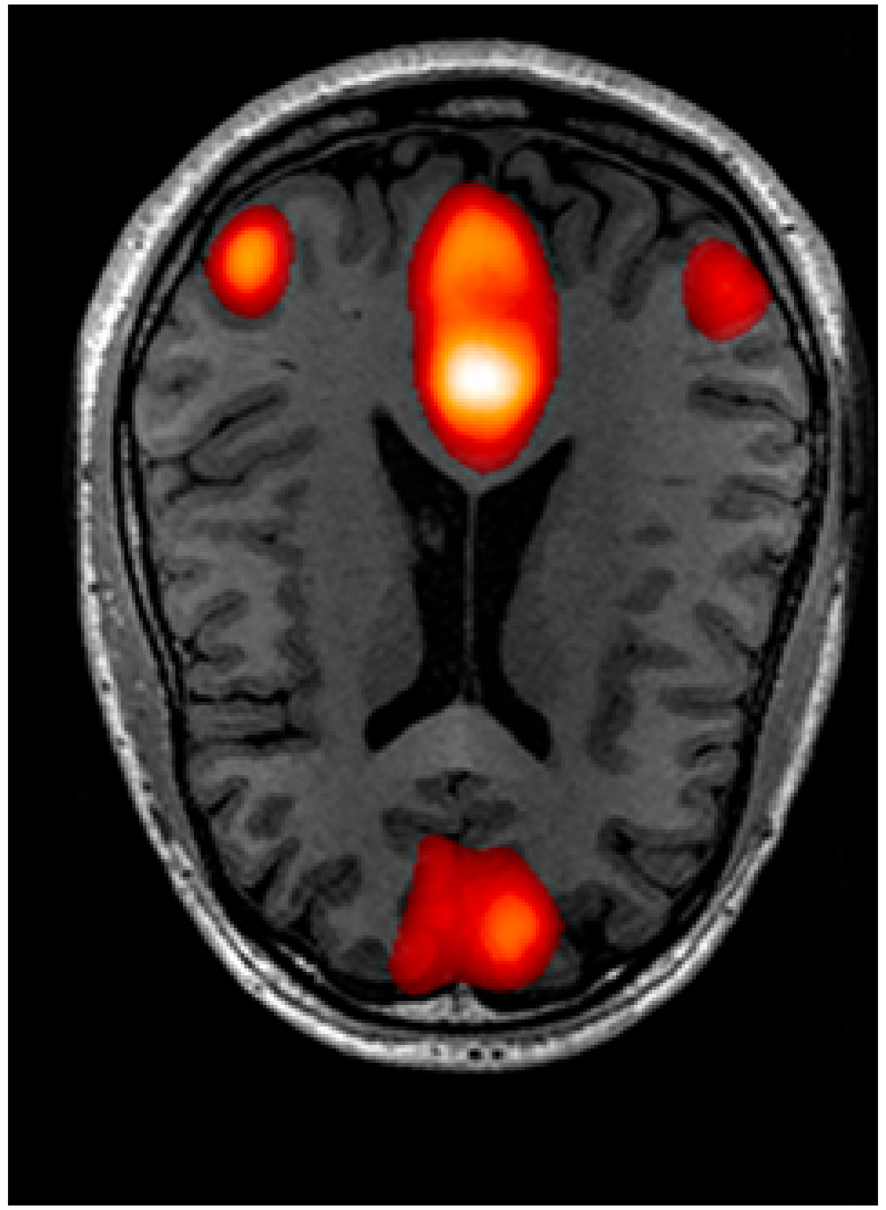




Brain Modes are Physically Significant

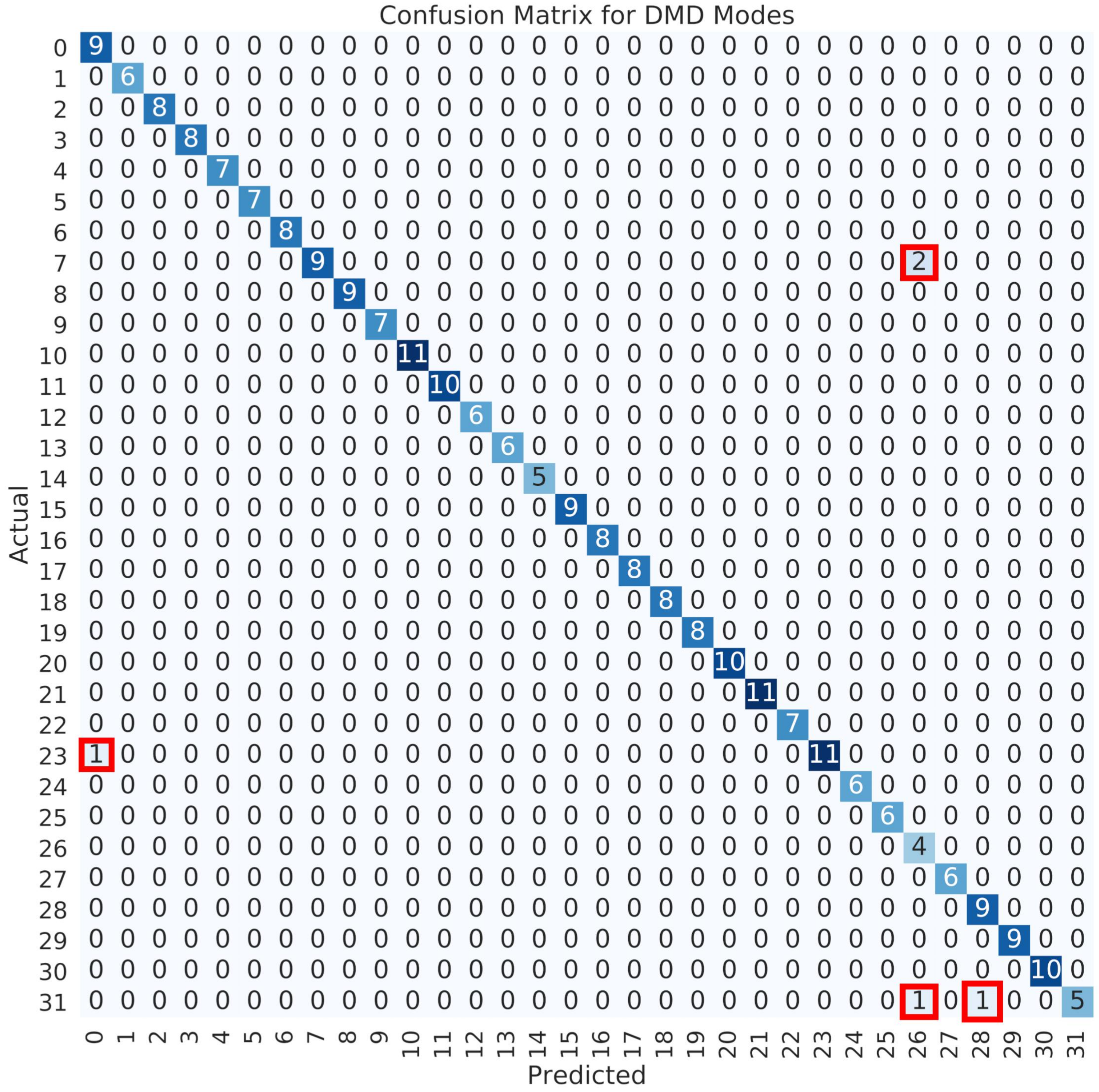
- An Eigenmode from 32 Channel EEG DEAP data

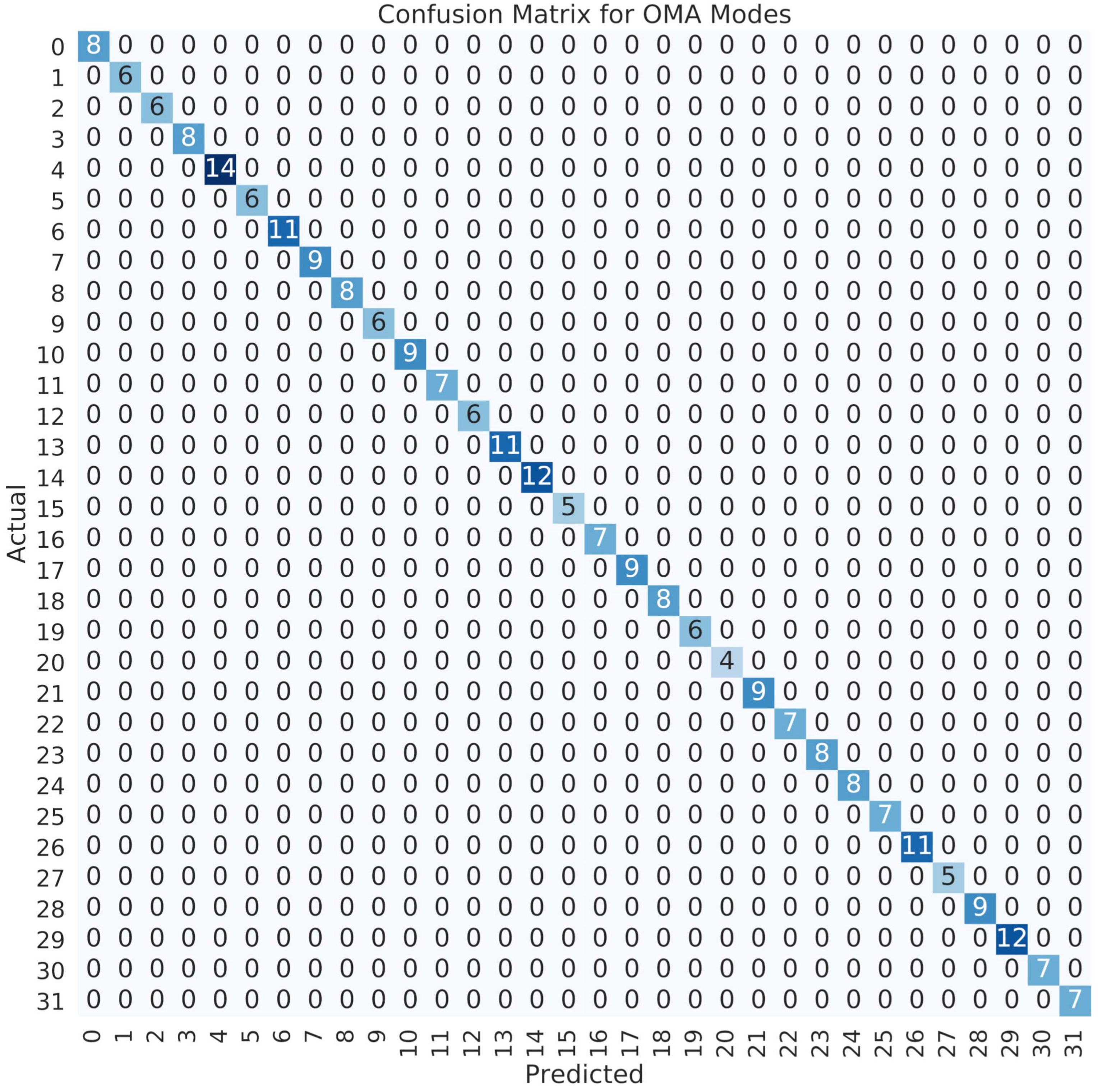




Brain Modes are Interpersonally Dependent

- Subject Identification from BW Modes (Random Forrest)





Some Brain Modes are not Interpersonally Dependent

Table 1: Common OMA Brain Modes

	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

Subject 1: Alpha Mode 1 Subject 2: Alpha Mode 1

Unique Aspects of the Approach

- Online
- Robust Features
- Spatio-temporal
- Linear systems

Assumptions and Corner Conditions

- Input is **unknown**, persistent
- Stationary
- Scaled
- Linear (!)

Linearity and the Brain

PHYSICAL REVIEW E, VOLUME 64, 061907

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

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(Received 14 May 2001; published 20 November 2001)

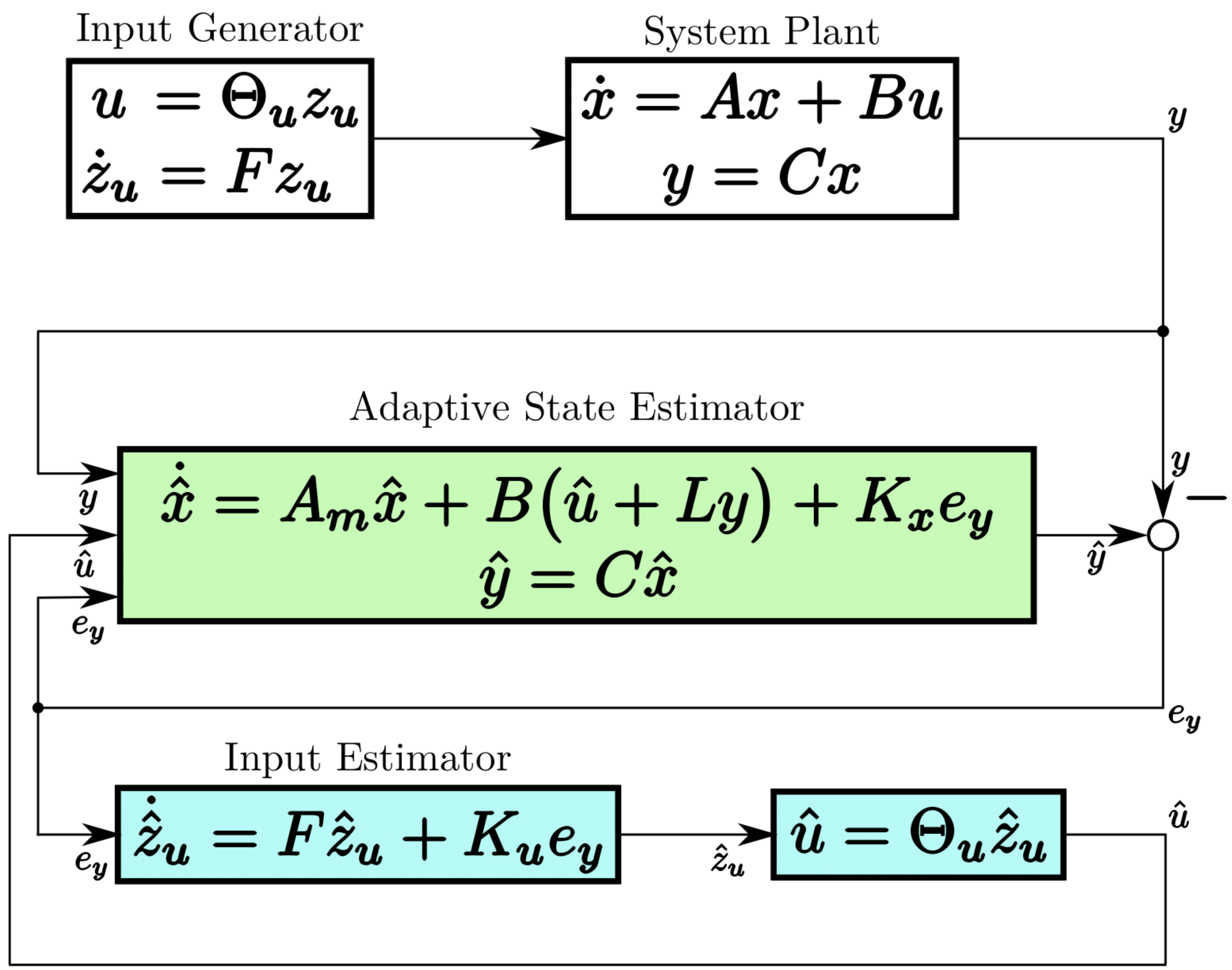
We compare dynamical properties of brain electrical activity from different recording regions and from different physiological and pathological brain states. Using the nonlinear prediction error and an estimate of an effective correlation dimension in combination with the method of iterative amplitude adjusted surrogate data, we analyze sets of electroencephalographic (EEG) time series: surface EEG recordings from healthy volunteers with eyes closed and eyes open, and intracranial EEG recordings from epilepsy patients during the seizure free interval from within and from outside the seizure generating area as well as intracranial EEG recordings of epileptic seizures. As a preanalysis step an inclusion criterion of weak stationarity was applied. Surface EEG recordings with eyes open were compatible with the surrogates' null hypothesis of a Gaussian linear stochastic process. Strongest indications of nonlinear deterministic dynamics were found for seizure activity. Results of the other sets were found to be inbetween these two extremes.

DOI: 10.1103/PhysRevE.64.061907 PACS number(s): 87.19.La, 05.45.−a, 05.45.Tp, 87.19.Xx

We Must Expect Non-Linear Effects

Leverage the model framework

An Adaptive Modal Approach



Adaptive UIOs

IMECE2021-67484

An Adaptive Control Framework for Unknown Input Estimation

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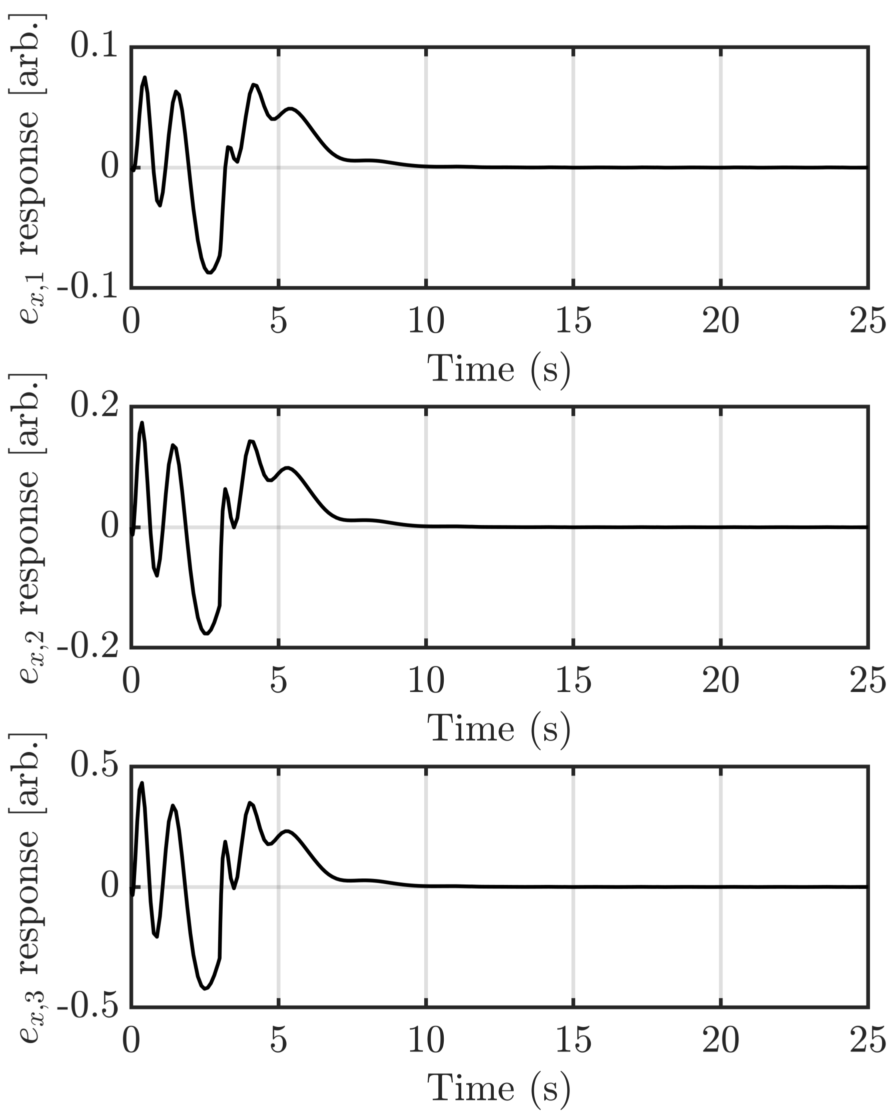
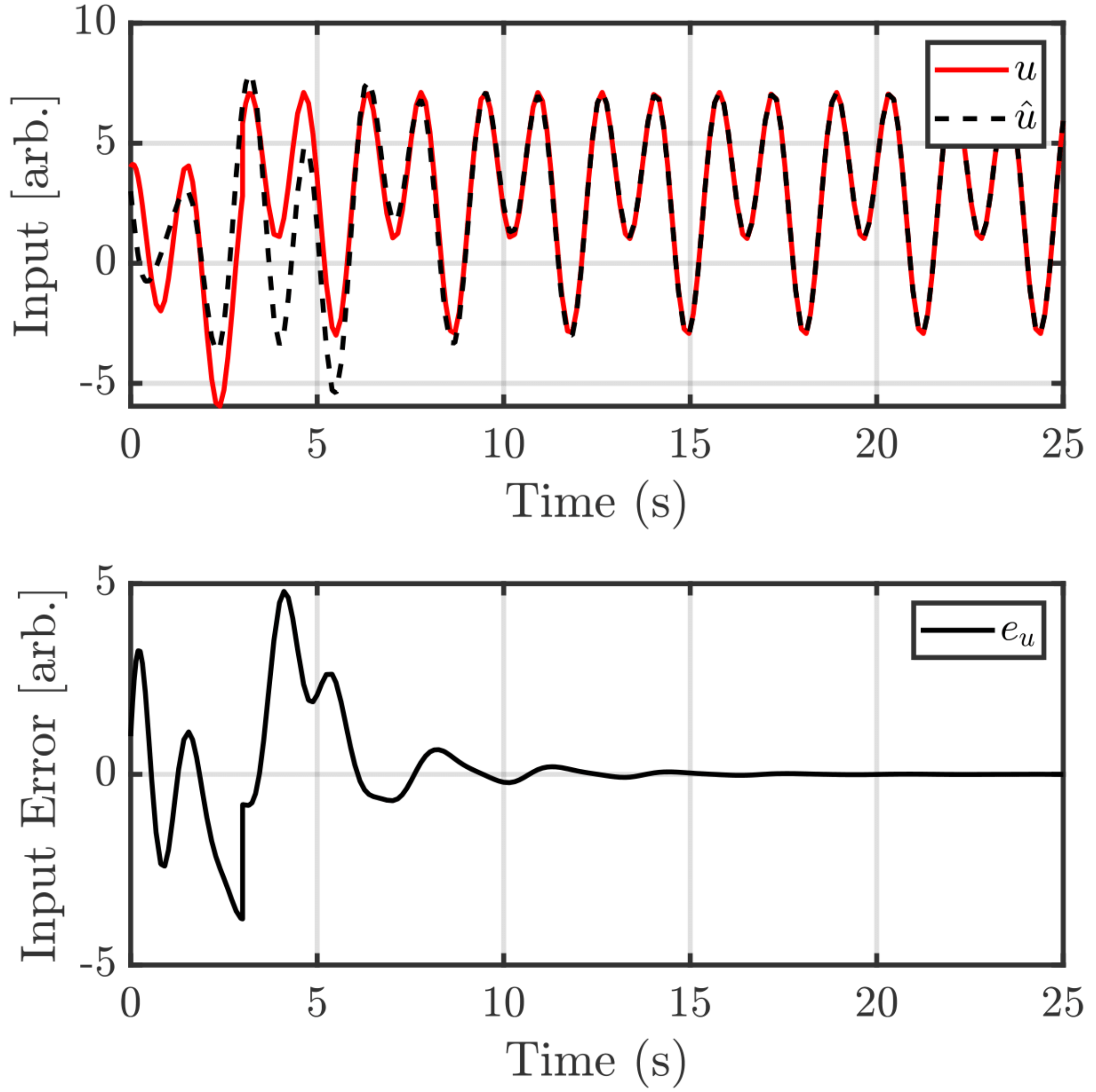
Input Generation

$$\begin{cases} \dot{z}_u(t) = F_u z_u(t) \\ \hat{u}(t) = \Theta_u z_u(t) \end{cases}$$

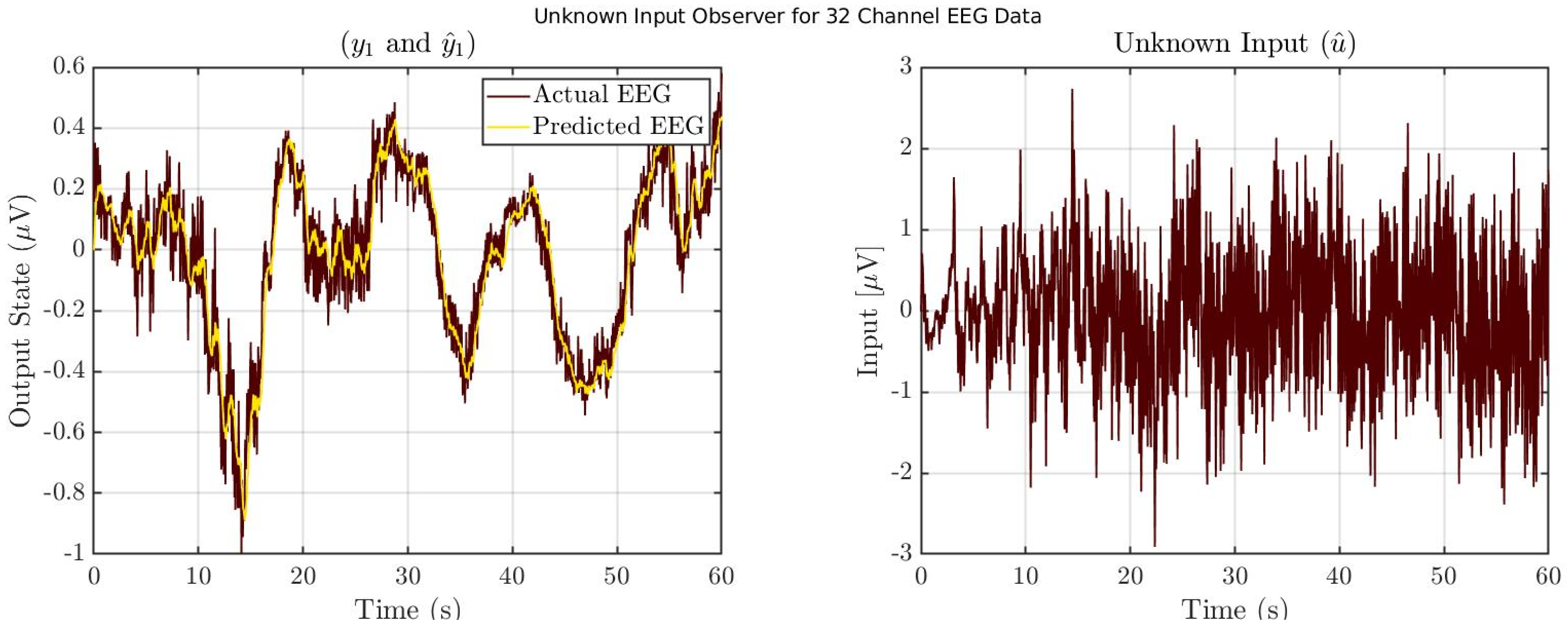
$$\begin{cases} \dot{z}_u(t) = \begin{bmatrix} 0 & 1 \\ -\omega^2 & 0 \end{bmatrix} z_u(t) \\ \hat{u}(t) = \begin{bmatrix} 1 & 1 \end{bmatrix} z_u(t) \end{cases}$$

- Toy UIO Example with Uncertain Dynamics





Adaptive UIOs for EEG



3. Timeline

Task Breakdown

- Modeling outcomes and affect
- Improve UIO fidelity
- Quantum extensions and decision making (stretch)

A Burst of Delight