Title slide

Outline

1. Intro and motivation

- Paradigm shift
- · Improved sensing, path planning, decision making
- Lots of human to computer, less computer to human
- Automation conundrum and teaming, bi-directional flow
- Are you paying attention???

Endsley quote

- · Historically simulation questionnaire
- Sensors and modeling moving towards physiological measures of human state/cognition

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.

Cognition is the black box

- · Improved modeling is needed
- Use canonical engineering approach
- Cognition acts on physiology, which is loosely tied to EEG

State of the art

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.

- Nonstationary signals make the *dynamics* tricky
- Phase and traveling waves
- This work seeks a method to address in engineering dynamics terms
 - with eye towards cognitive outcomes

Guardrails

What we're not saying:

- this models the brain
- · this models the cellular activity

What we are saying

- Beam and atoms vs. brain waves and neurons
- You can measure this dynamic signal and say something engineering about the system

2. A Dynamic Systems view

• start to introduce the structure and approach

Important EEG details

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

A canonical approach

- Have these difficult signals, nonlinear and not independent and nonstationary
- We impose this structure, consider \$A(t)\$

level is an unsolved

- We can't not know everything
- · but we do
- SO
- first identify the linear structure
- around an operating point
- realizing that the unknown input and nonlinear leaks thru
- uncertainty in A_m bc C_m would be equivalent

treating nonlinear

- Lots of works says this is a nonlinear nonstationary system
- We introduce a nonlinear nonstationary estimator that updates the model in real time

Modes elegantly capture

- Giant (A,B,C) isn't useful for analysis
- · modal transform is equivalent
- similarity
- yields discrete set of spatio-temporal modes which have...

3. Sys Id using EEG

With that overview, how do we extract that first step, the linear operating point...

Considered algorithms

- We want to extract those *linear* patterns from the data
- · Looked at 4 that give right structure
- For time, OMA only bc
 - classification
 - consistency
 - Numerical algorithm for Subspace State Space System IDentification

OMA theory

- A discrete time plant looks like this
- If we knew size of C and initial condition...
- LEFT AND RIGHT SINGULAR VECTORS
 - FILLING IN THE DISTRIBUTION

Truncation

- We don't need to work with full order model
- about 40-50 modes for EEG stuff

EX

- · see that it works
- · see that it yields physically interesting models

4. Modal Analysis of Brain Wave Dynamics

- · Remember, linear model of nonlinear system
 - Is it useful???
- Analysis

Traveling vs standing

- When do waves reach peak?
- a function of uneven damping
- negative damping
- indicates different regions doing different tasks

Common modes

Find four out of 40 to be task independent

Interindividual

- use modes to id individual
- seem to act as a finger print
 - o on our data

BUT

- · they don't match the future dynamics
- if you can go back in time, vs forward

5. aUIO

we've got a problem. address with full architecture somewhat removed from EEG

Est overview

- u is exogenous, determenistic, something modes can't generate
- v_x is a nonlinear, nonstationary
 - o not restricting it to white

modeling ui

- it's too much to simply id the waveform
- select basis persistent based on engineering
- · id coefs instead of waveform

arch and estimator error

- recover A
 - update based on error
 - o alpha is a filter on update
 - gamma_e is a tunable positive matrix
- · know little about top

arch

- given ASD, stable transmission zeros you can find this
- · notice, bound on v and alpha define convergence rate

lil example

6. Reconstructing the Brain's Unknown Input

First things

this really really works

it's bc of the adaptation in the modes

details

- ui acts evenly, Linear ind and smearing
- sine cos is physically sig
- · LQR gains

curious

- modes from another person
- not any hurwitz, but any eeg modes
- you can tolerate some slop in the modes
 - convergence is the primary effect

classification

- We hypothesize
 - modes are correlated with human state/cognition, so
 - same state should have similar modes, so
 - you can take the average modes in a state,
 - and the estimator will perform better than the other state
- DEAP dataset and self report
- binary and interindividual

results

- on par with modern DL
- · computation much less
- · analysis much more
 - more than total lifetime footprint of 5 cars

7. Konks

Ack