Computational Modelling of Cognitive Functions using EEG Data

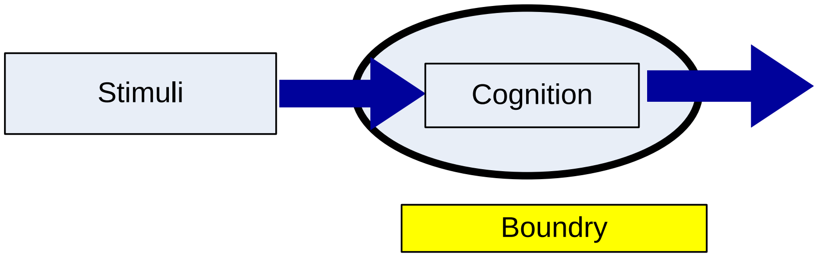
Student:
Nabaraj Dahal
Supervisors:
Prof. Nanda Nandagopal
Prof. Javaan Chahl
Prof. Paul Gartner
Dr. Zorica Nedic
Dr. Mark McDonnell

Outline

- Background
- Objective and Approach
- Parametric modelling using TVAR with Kalman smoother
- Distraction Experiment with Driving Simulator
- Event Related Synchronization / Desynchronization
- Results
- Conclusion and Future work

Background

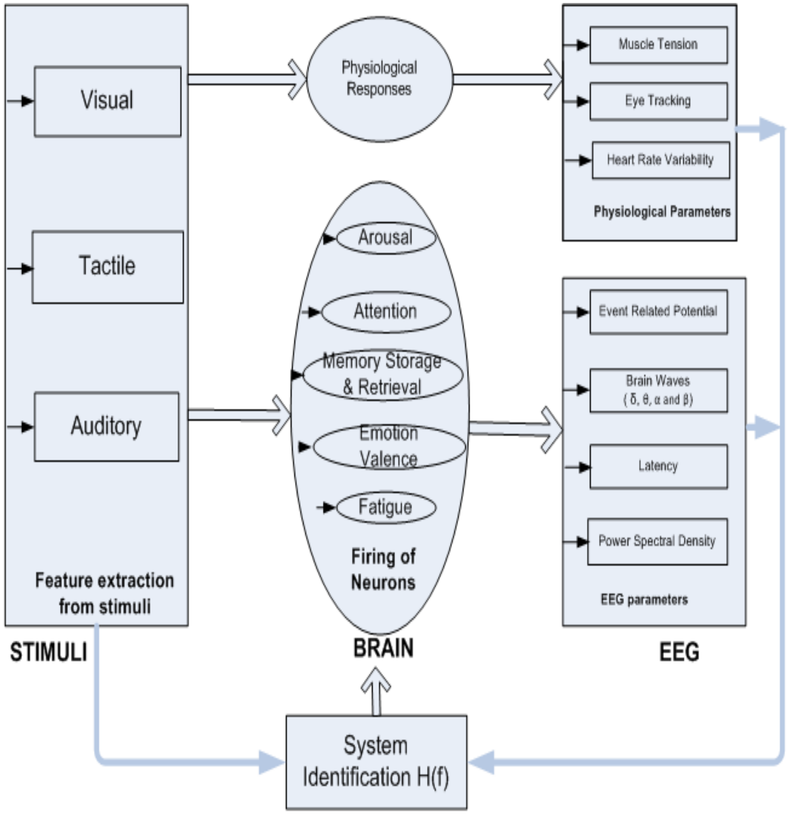
- Cognition
  - Computing massive number of processes inside the brain



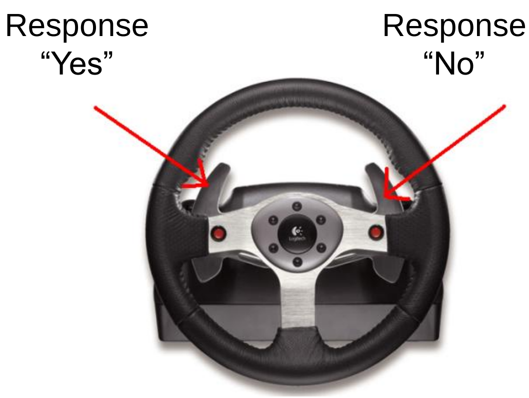
- Physiology behind the encoding, storage, retrieval and decision making?
- Applying mathematical models and Engineering tools- Reverse Engineering
- Represent cognitive functions from EEG responses to stimuli

Objective/Approach

- To investigate methodologies and techniques to model the human cognitive function using EEG responses to a set of cognitive stimuli
- To stimulate Cognition in Driving Scenario



Cognitive Load Lab Experiments: Distraction Experiment with Driving Simulator



5U

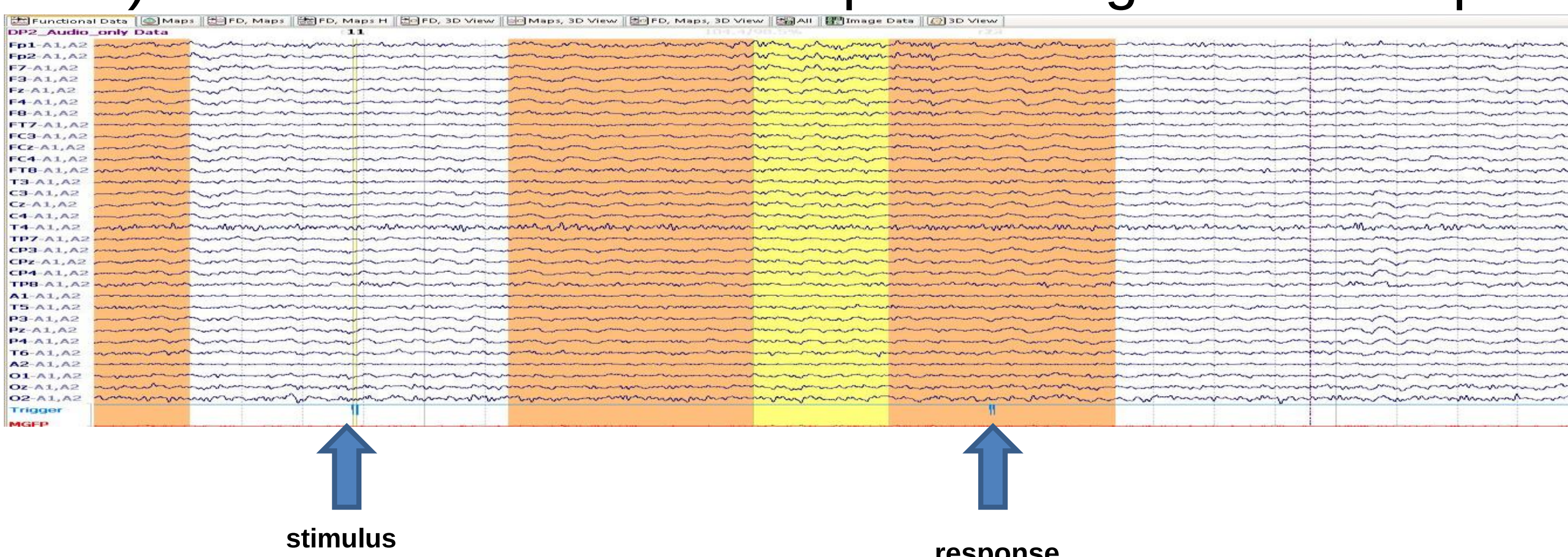
B8

Data Acquisition

- EEG Equipments:
  - NuAmps Amplifier
  - Curry Acquisition System
  - STIM2 stimulation provider system
  - Triggers of stimuli and responses
- Recording Criteria:
  - 30 EEG channels, 2 reference channels, 1 trigger channel
  - 1000 Hz (sampling rate)
  - 1 Hz -70 Hz with 50 Hz notch filter

Pre-processing

- Blinks detected using template matching and corrected using Independent Component Analysis.
- EEG chunks where response time falls between 500 and 3000 ms only selected.
- 2 sec chunks(Trials) after the stimulus (500 ms to 2500 ms) were selected for further processing – 256 Samples



Parametric Modelling of EEG data

- AAR/ TVAR (Adaptive/Time-Varying Auto Regressive Model) has been extensively used
  - Captures EEG pattern effectively
  - Improves classification accuracy
- TVAR equation realized in state space model enables use of Kalman filter
- Kalman smoother uses future measurements available to further improve (smooth out) estimation performance

TVAR model for EEG

- EEG sequence: $$y_t = \sum_{k=1}^{p} a_k^{(t)} y_{t-k} + v_t \qquad (1)$$

$\{a_k^{(t)}\}_{k=1}^{p}$ are TVAR coefficients, p is the model order, v_t is Gaussian noise with zero mean and variance σ_v^2 .

- TVAR coeffs follow Gauss Markov model:

$$\mathbf{x}_{t+1} = A\mathbf{x}_t + \mathbf{w}_t \qquad (2)$$

$x_t = [a_1^{(t)} a_2^{(t)} \ldots a_p^{(t)}]'$ *is the array of TVAR coeffs*

$w_t \sim N(0, Q)$ *is the i.i.d Gaussian noise*.

A is the transition matrix.

- In State Space Model:

$$\text{Measurement Equation} : y_t = \mathbf{h}_t' \mathbf{x}_t + v_t$$

$$\text{State Equation} : \mathbf{x}_{t+1} = A\mathbf{x}_t + \mathbf{w}_t$$

$h_t = [y_{t-1} y_{t-2} \ldots y_{t-p}]'$ *is the vector of past p measurements.*

TVAR Coefficients

- The initial state is assumed Gaussian: $x_0 \sim N(\mu_{0,} \Sigma_0)$
- Model parameters will be:

$$\Theta \equiv \{A, \sigma_v^2, Q, \boldsymbol{\mu}_0, \Sigma_0\}$$

- The model parameters are estimated using Expectation maximization (EM) algorithm proposed by Khan& Dutta, 2007.
- The EM algorithm based Kalman Smoother(Khan & Dutta, 2007) gives the AR coeffs that captures the dynamics of EEG much better.

TVAR Coefficients with Kalman Smoother

- Forward recursion equations:

$$x_{t|t-1} = Ax_{t-1|t-1}$$

$$P_{t|t-1} = AP_{t-1|t-1}A' + Q$$

$$K_t = P_{t|t-1}H_t'(H_t'P_{t|t-1}H_t + \sigma_v^2)^{-1}$$

$$x_{t|t} = x_{t|t-1} + K_t(y_t - H_t'x_{t|t-1})$$

$$P_{t|t} = (I - K_tH_t')P_{t|t-1}$$

- Backward recursion equations:

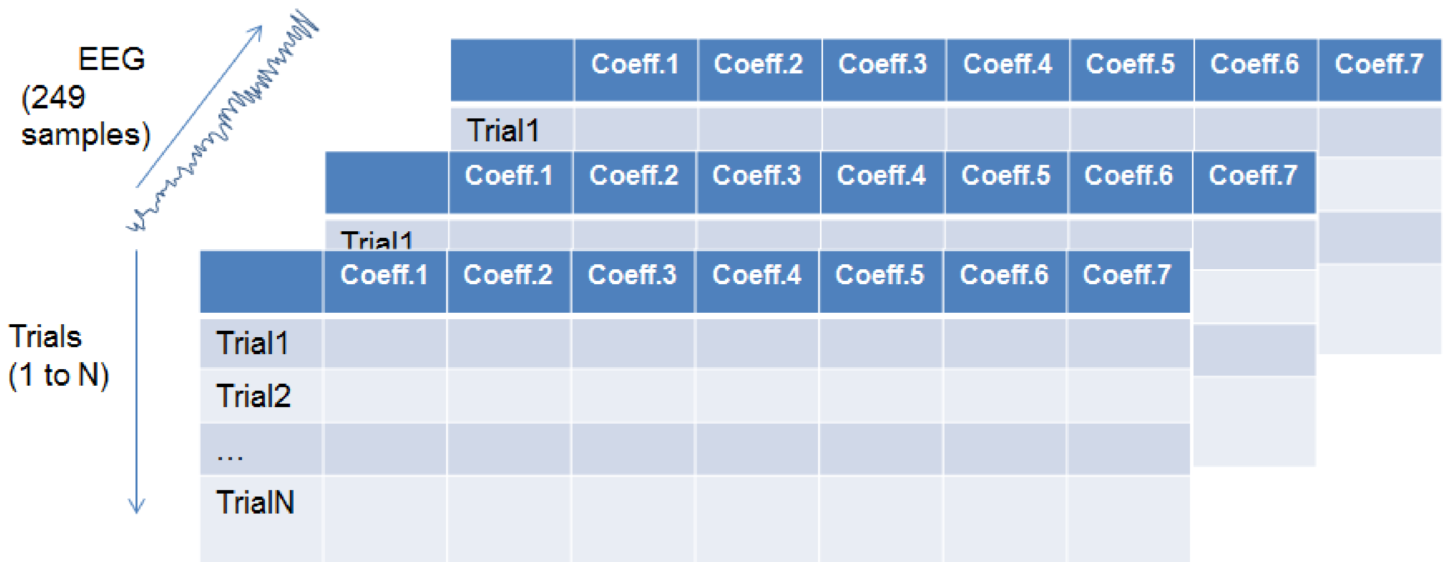
$$J_t = P_{t|t}A'P_{t+1|t}^{-1}$$

$$x_{t|\mathrm{T}} = x_{t|t} + J_t(x_{t+1|\mathrm{T}} - x_{t+1|t})$$

$$P_{t|\mathrm{T}} = P_{t|t} + J_t(P_{t+1|\mathrm{T}} + P_{t+1|T})J_t'$$

TVAR Modelling using Kalman Smoother

- Order of filter chosen:7
- 7 AR coefficients are predicted for each sample of each trials.



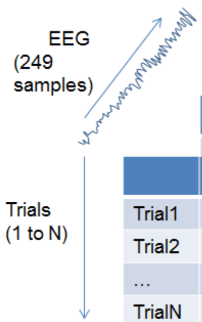
All Pole Modelling using TVAR Coefficients

- The AR coefficients of each samples are averaged over all the trials.
- 7 TVAR coefficients at each time instant from (8 to 256 samples).
- The transfer function of the AR model:

$$G(z) = \frac{1}{1 + \sum_{k=1}^{p} a_t^{(k)} z^{-k}} \qquad (3)$$

- The poles of the model are given by the roots of the denominator.

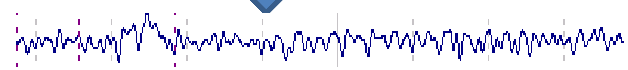
All Pole plot for ONE Channel



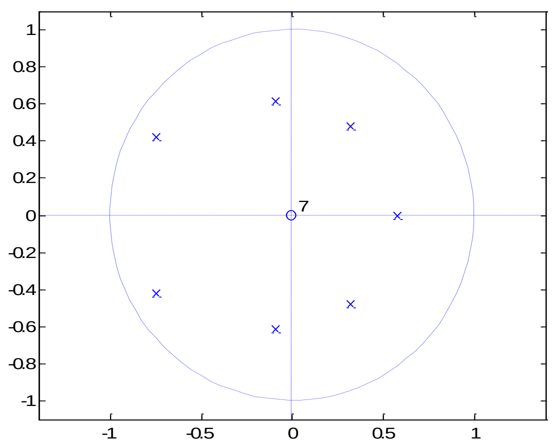
	Coeff.1	Coeff.2	Coeff.3	Coeff.4	Coeff.5	Coeff.6	Coeff.7
Trial1							
Trial2							
…							
TrialN							

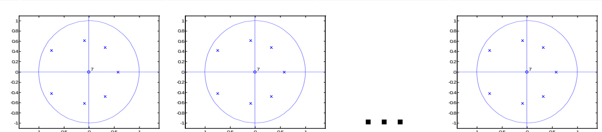
	Sample1	Sample2	…	Sample249
Coeff.1				
Coeff.2				
…				
Coeff.7				

Pole calculation

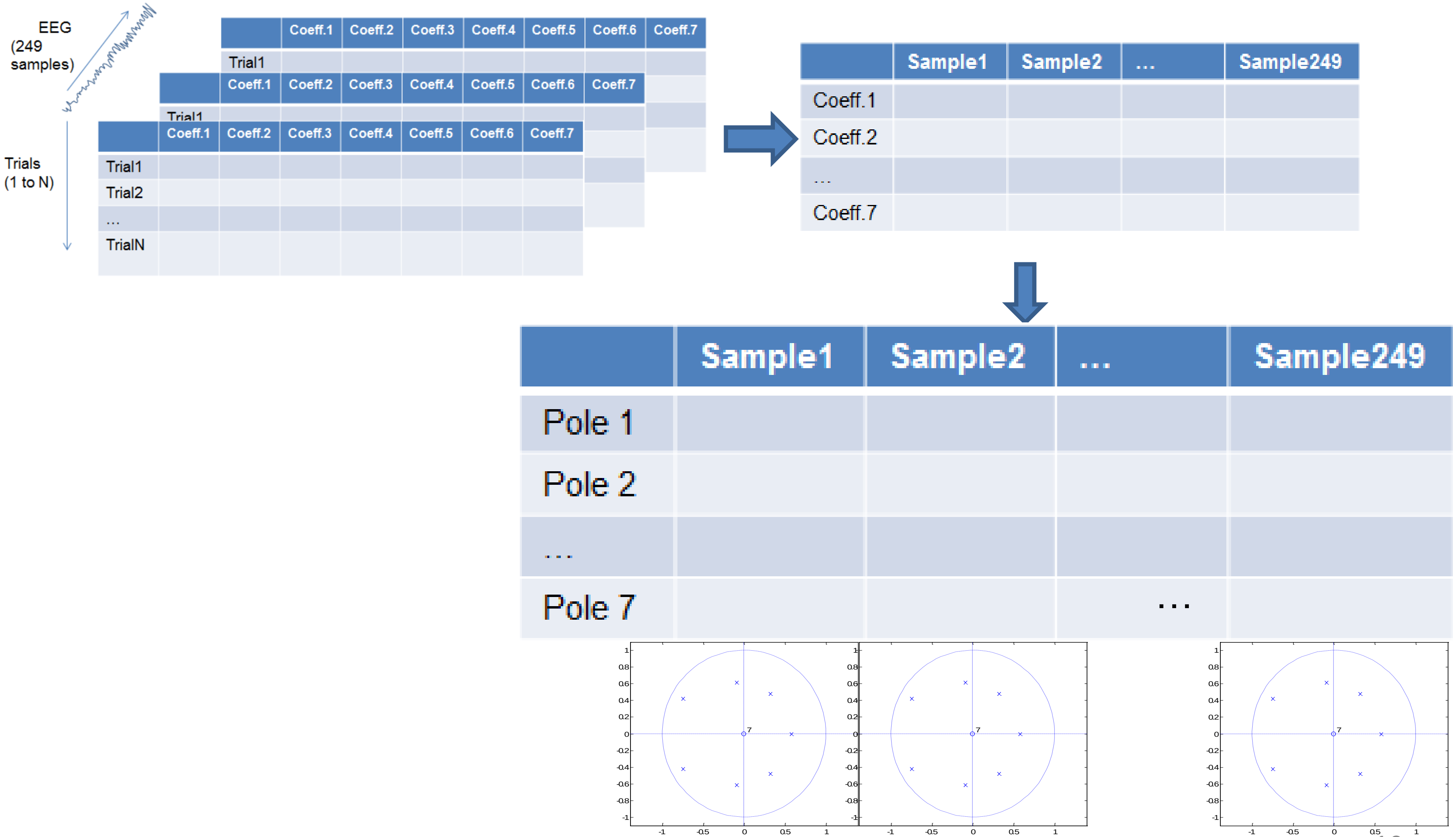


	Sample1	Sample2	…	Sample249
Pole 1				
Pole 2				
…				
Pole 7				

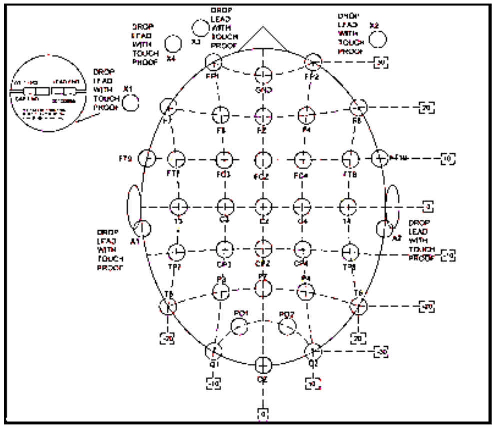


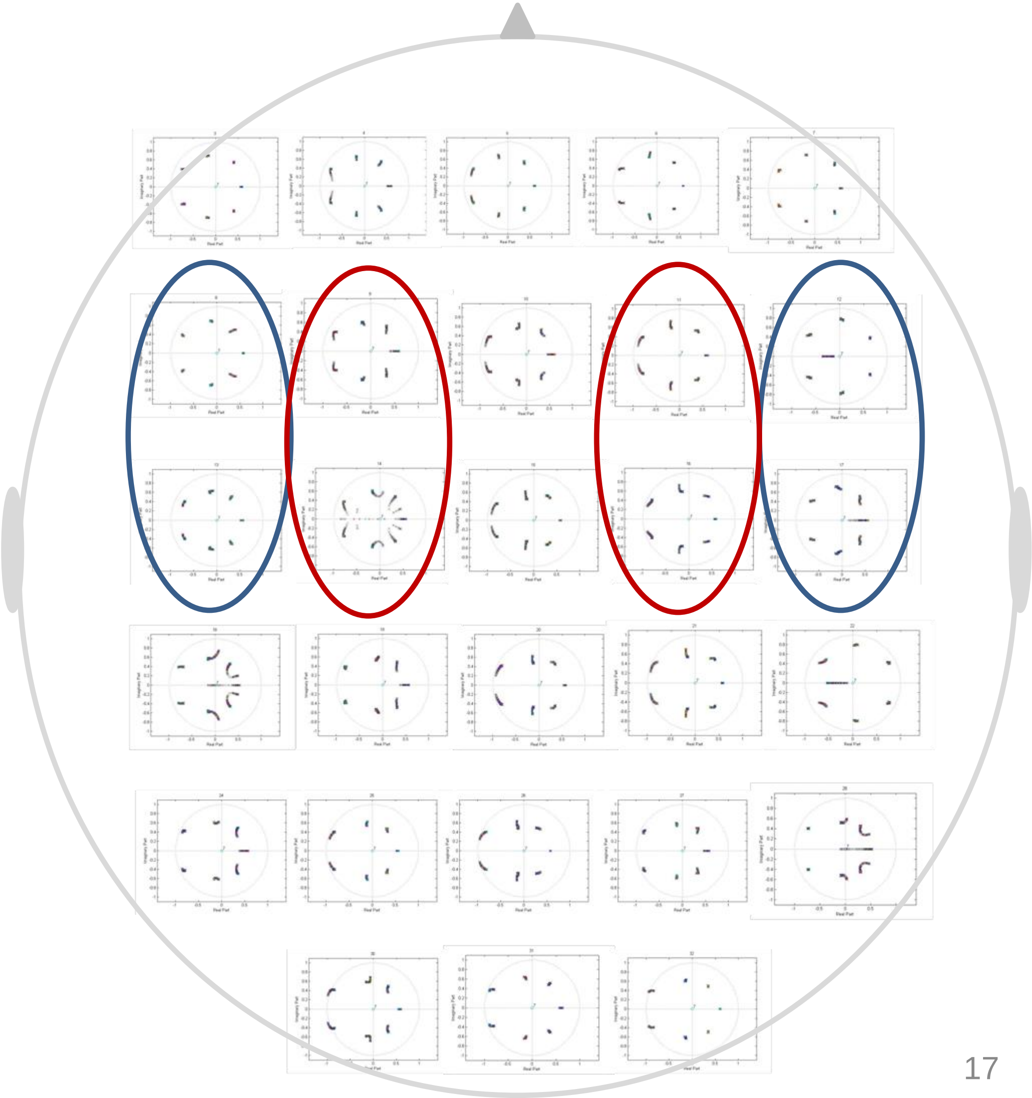


All Pole plot for ONE Channel



All Pole plot for all channels



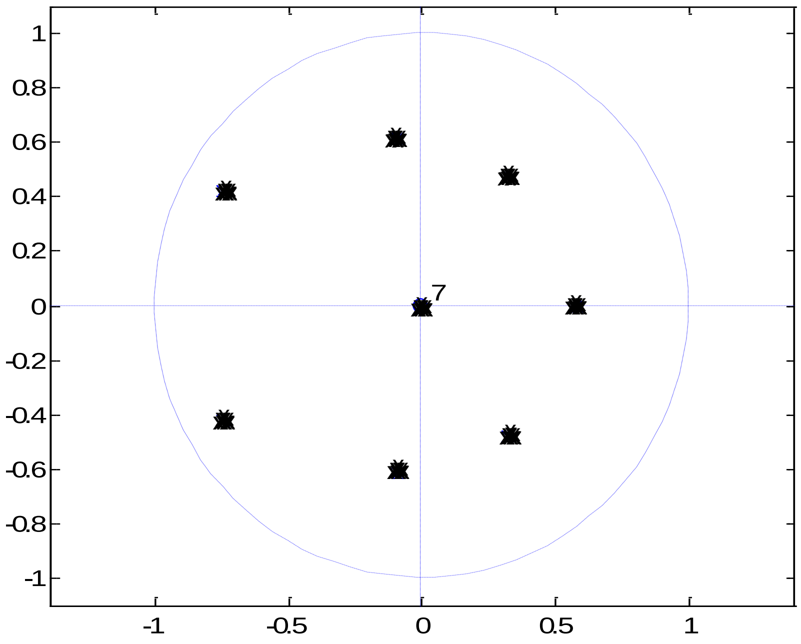


Event Related Synchronization/Desynchronization

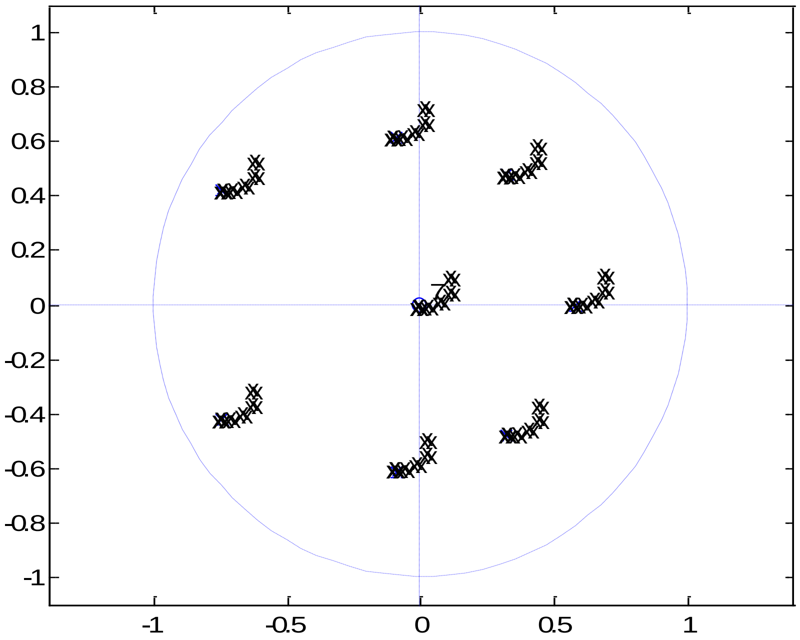
- Increase or decrease in power in specific frequency band
- The cause is believed to be the increase of decrease of the synchrony of the underlying neuronal population.
- ERP-time locked EEG activity
- ERS/ERD- phase(frequency) locked activity

Synchronization/Desynchronization

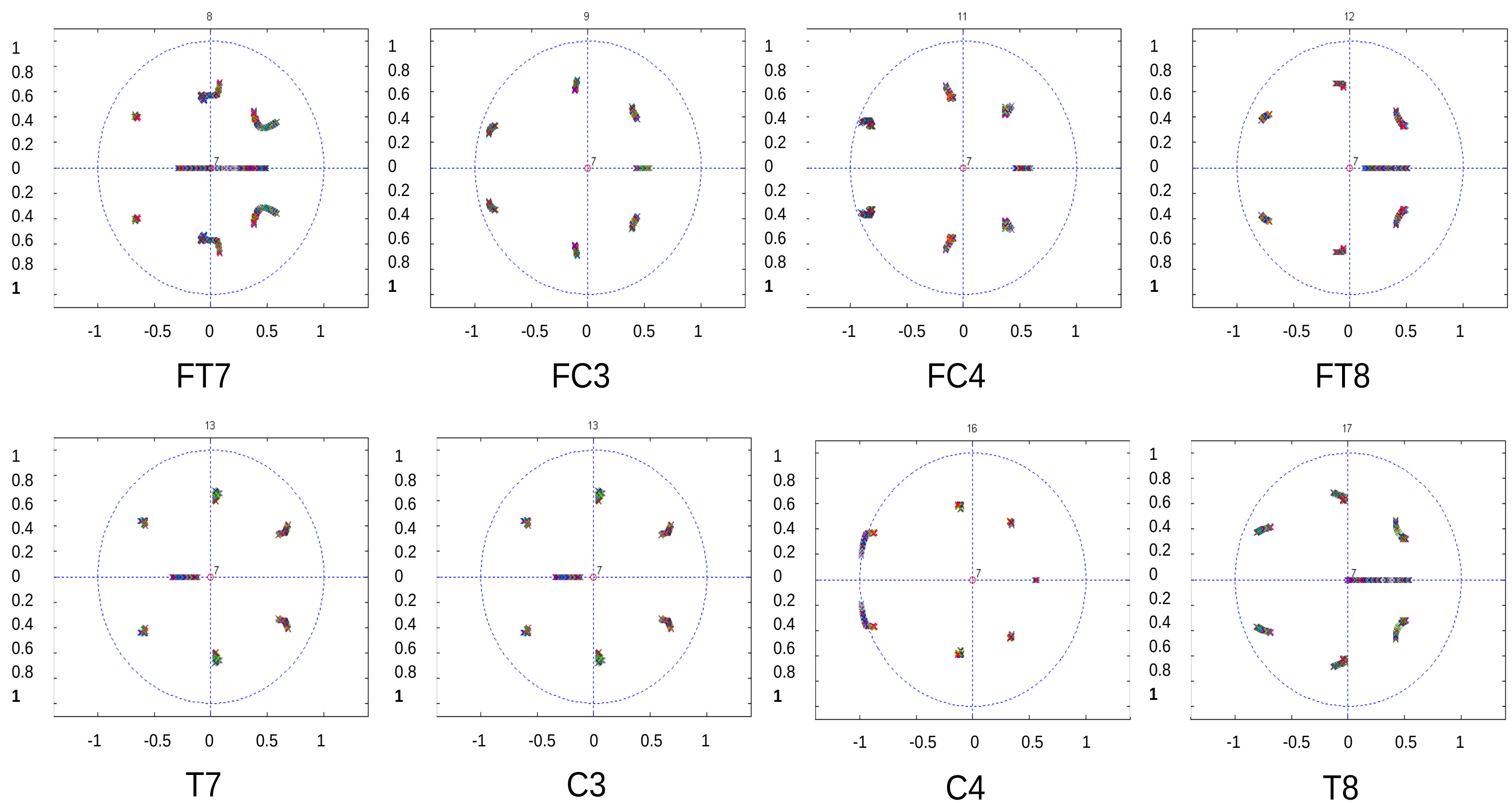
Synchronization



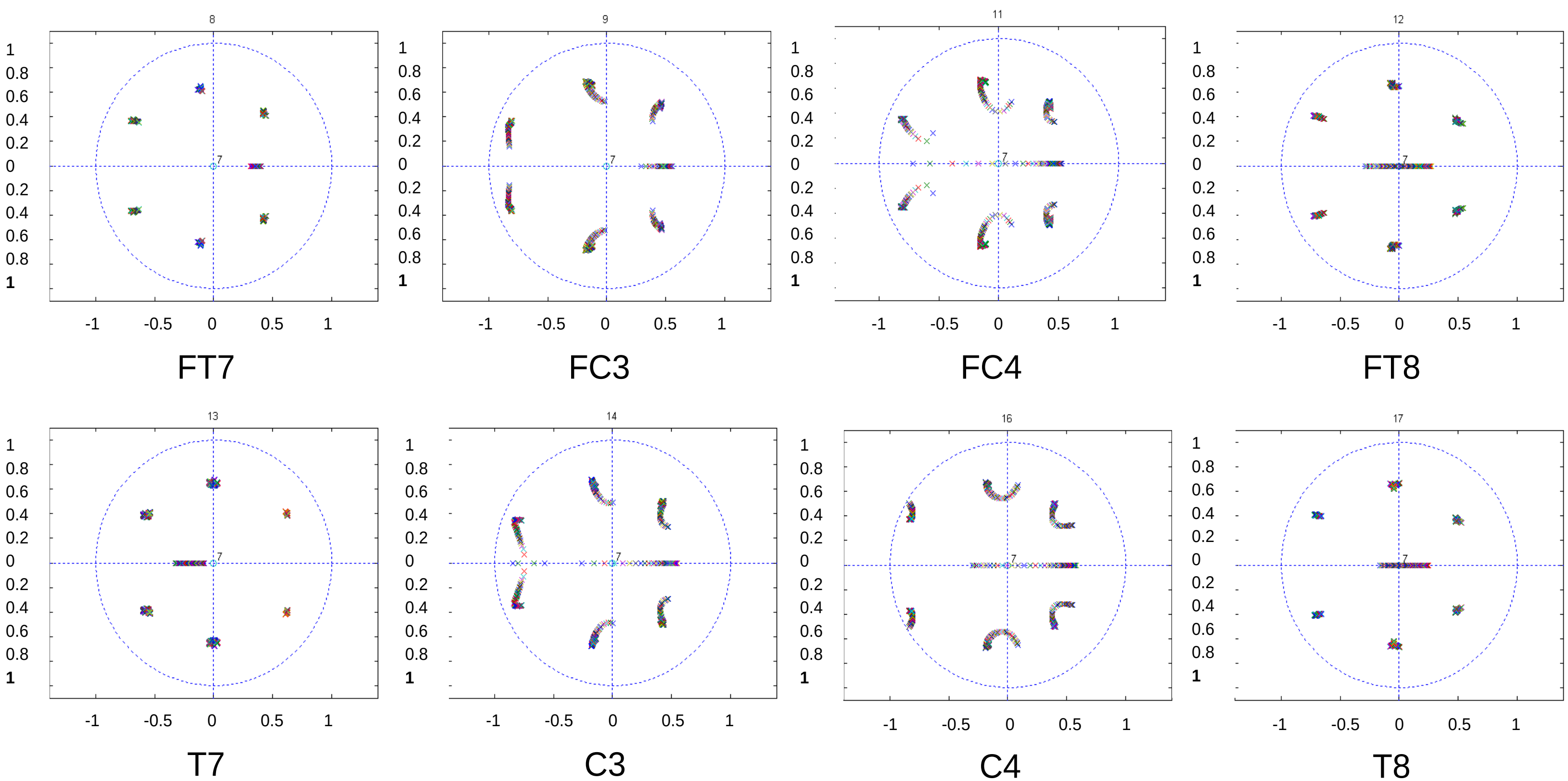
Desynchronization



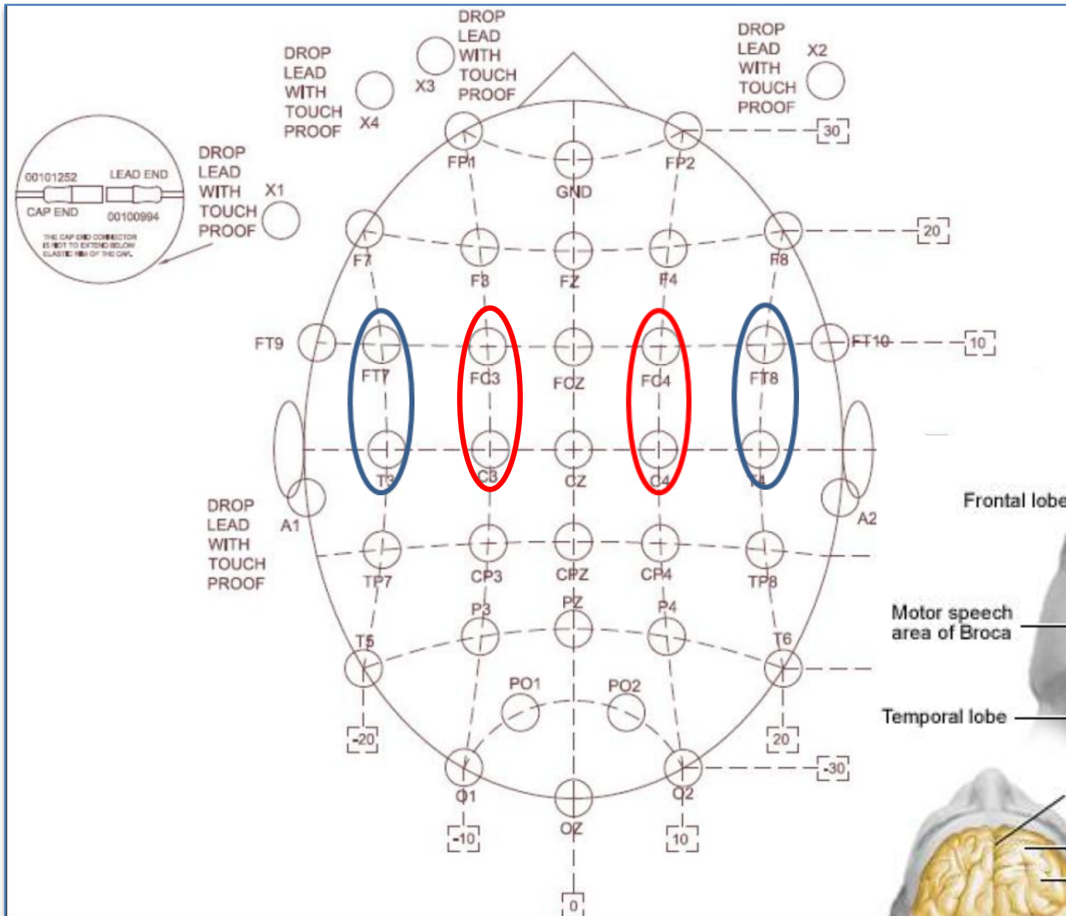
Driving Only Results

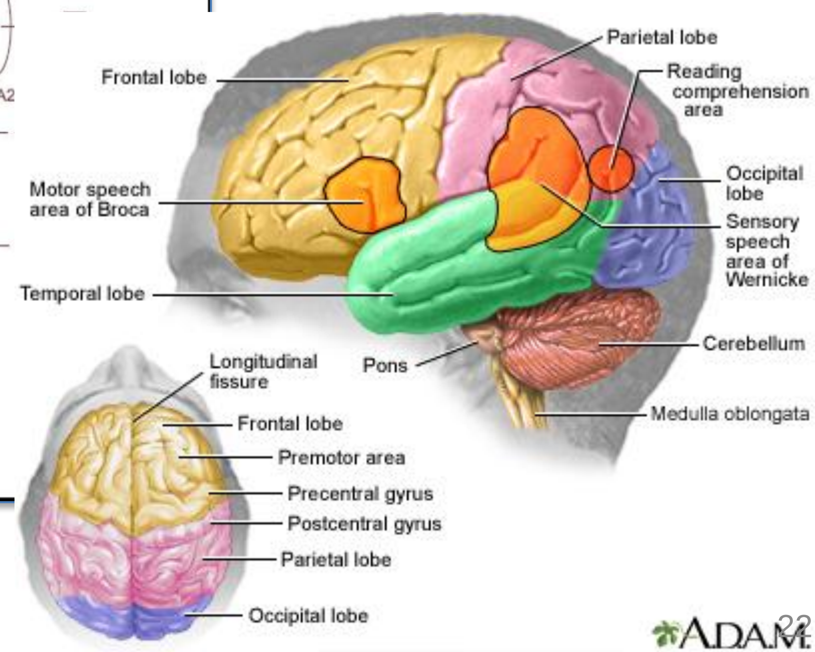


Audio Distraction Driving Results



Results with Audio Distraction





Conclusions and Future Work

- Conclusion:

  Pole analysis of a TVAR model is a sensitive and practical technique for visualizing ERS/ERD patterns.

- Future Work:
  - Use the poles consistency and variations as feature Vector to build a model.
  - Classify feature vector for distracted driving from base driving.
  - Identify feature vector during visual distracted driving.
  - Proceed to other cognitive functions like arousal, fatigue, memory, emotion in driving


Thank You!