Assessing Cortical Network Dynamics with Multiplex Visibility Graphs

Arya Teymourlouei[1], James Reggia[1,3], Rodolphe Gentili[2,3,4]

[1]Department of Computer Science, [2]Department of Kinesiology, [3]Neuroscience and Cognitive Science Program, [4]Maryland Robotics Center

Introduction

- To improve our understanding of the neural mechanisms associated with mental workload, studies have used electroencephalography (EEG) to analyze neural activity during task completion
- Cortical dynamics of mental workload have traditionally been analyzed through regional activity with EEG spectral power
- This is useful; however, prior work has shown cognitive processes involve interactions between brain regions
- To address this, functional connectivity (FC) methods have been developed. These study the statistical relationship between two brain regions
- Existing FC methods include imaginary coherence (IC) and weighted phase lag index (WPLI)
- The goal of this research to investigate the ability of a new graph-based method based on multiplex visibility graphs (MVGs) to assess FC dynamics

Methods

- EEG data was used from the COG-BCI database [1]
- Participants ($n = 29$) completed the Multi-Attribute Task Battery (MATB) under three levels of difficulty
- EEG was preprocessed with high-pass filter and independent component analysis (ICA)
  - Note: ICA was not used for the classification
- Five frequency ranges used: theta (4-7), low-alpha (8-10), high-alpha (11-13), beta (14-29), gamma (30-40)
- Three connectivity measures were with preprocessed EEG: WPLI, IC, and layer entanglement (LE)
- The LE method was recently introduced [2]:
  1. The natural visibility graph (VG) algorithm is used to map an EEG time series to a complex network [3].
  2. The VG of each EEG channel is assembled into the layers of a single MVG.
  3. The edge overlap between all layer pairs is computed and assembled to a layer entanglement (LE) matrix [4].
- To assess the consistency of the connectivity metrics across multiple (identical) study sessions, we compute two metrics: Pearson's correlation coefficient, and the repeatability [5]:

$$\mathrm{RE} = 1.96\sqrt{\frac{\sum_{i=1}^{n}(x_1 - x_2)^2}{n-1}} \qquad x_1 = \text{session 1 metric} \quad x_2 = \text{session 2 metric}$$

- We also assessed the ability of the connectivity metrics to classify different levels of mental workload to the levels of task difficulty
  - Ternary: three levels, binary: two levels
- Three classifiers were used: support vector machine (three variations of the kernel), random forest, and multi-layer perceptron
- Classification performance assessed with accuracy, computed for each participant, with cross-validation

Results

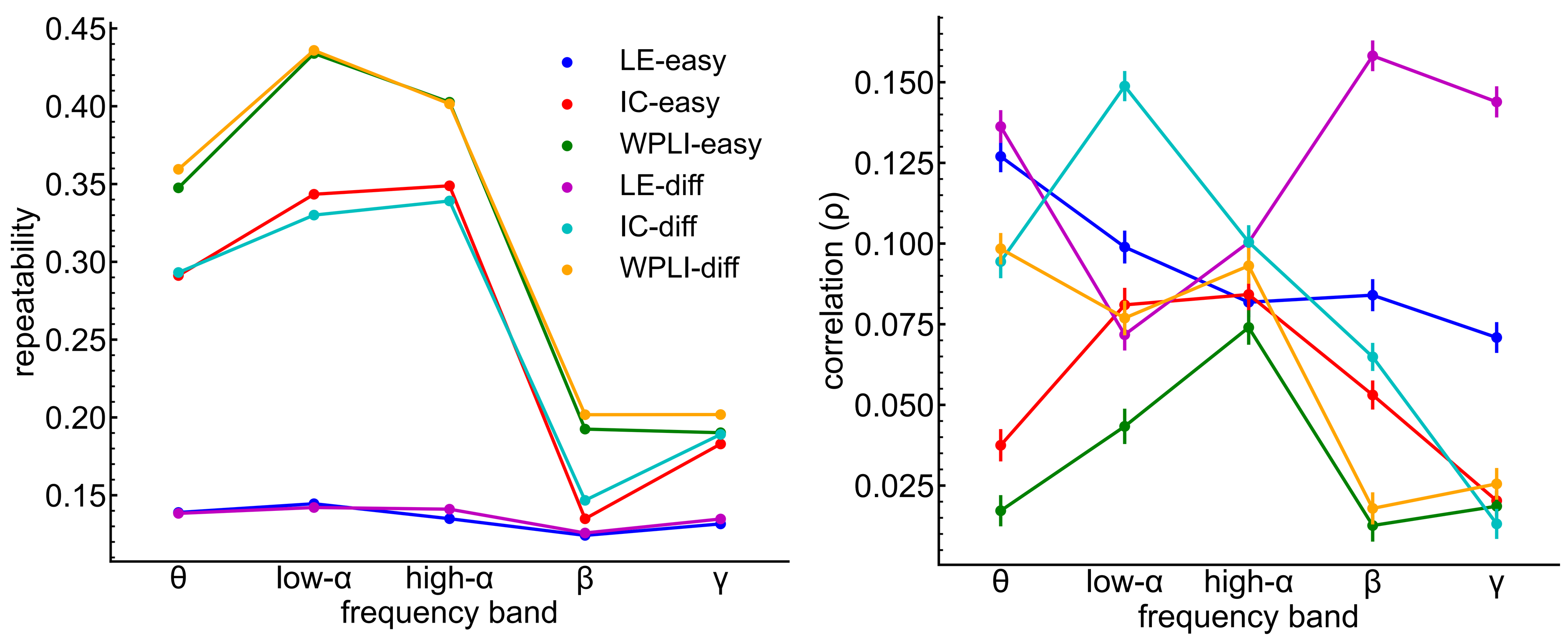

Fig 1. *Left plot*: Results of repeatability (the measurement error between two data collection sessions) across five frequency ranges, for three connectivity measures. Left plot: Results with the easy task condition. *Right plot*: Associated results for correlation coefficient (ρ).

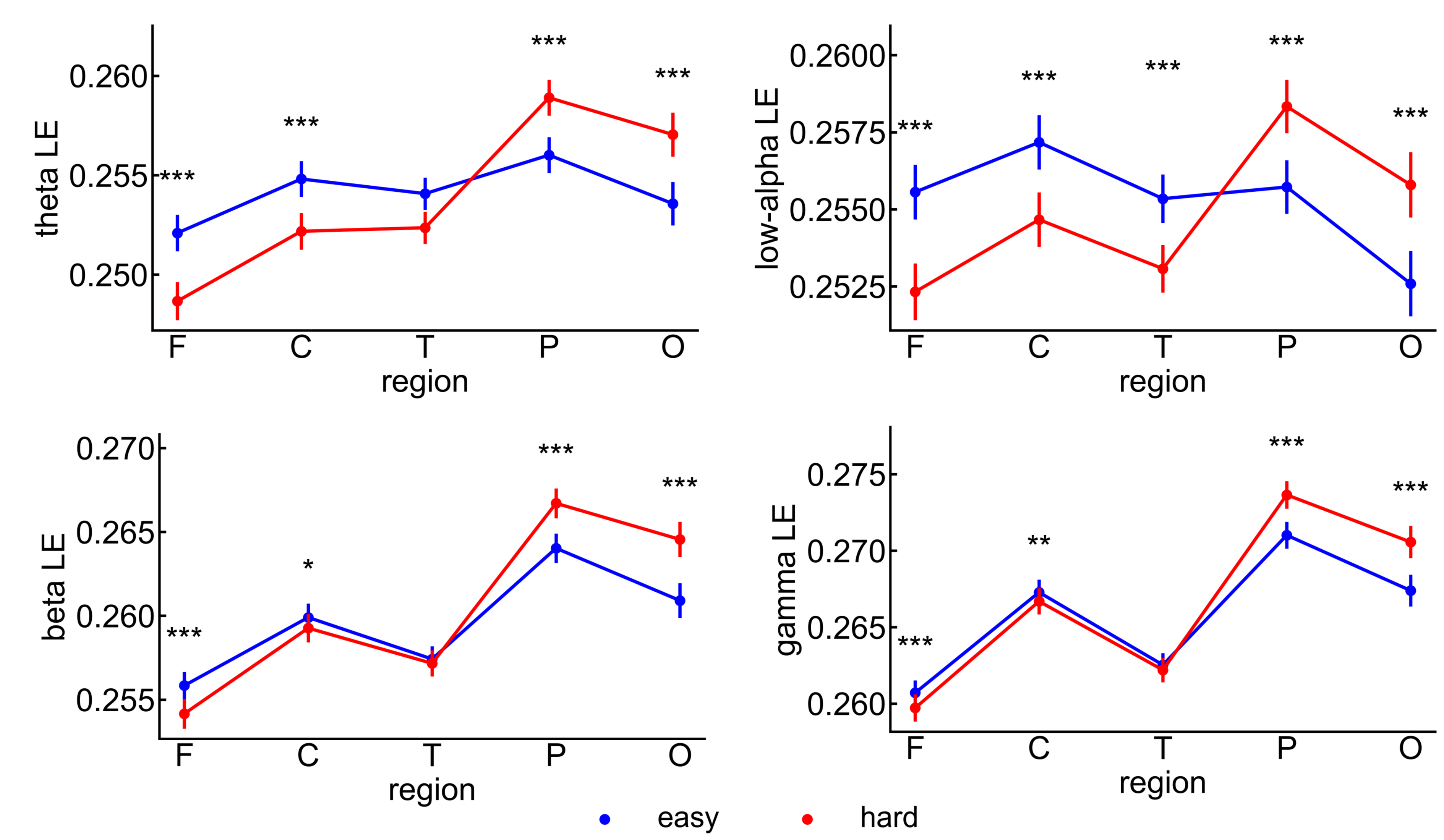

Fig 2. Statistical analysis of LE across five EEG sensor regions (frontal, central, temporal, parietal, occipital), presented for four frequency ranges: theta (top-left), low-alpha (top-right), beta (lower-left), gamma (lower-right). Legend denotes MATB task difficulty. Statistical significance: *p<0.05, **p<0.01, ***p<0.001.

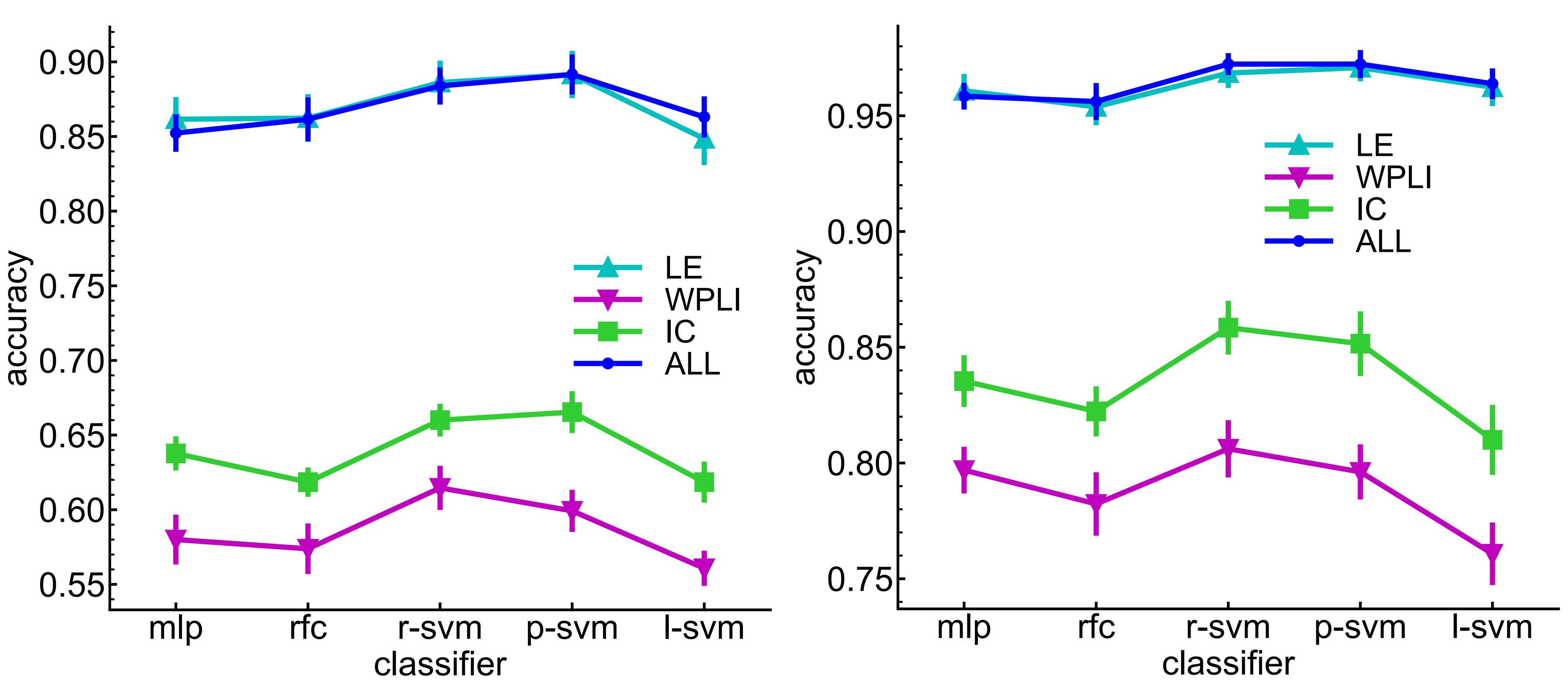

Fig. 3. *Left panel*: accuracy scores of five classifiers (multi-layer perceptron, random forest, RBF-SVM, polynomial-SVM, linear-SVM) tasked with predicting three levels of mental workload. *Right panel*: associated scores for predicting only two levels of workload.

Discussion

- Preliminary evidence was shown that the LE method has better repeatability than other FC methods due to lower measurement error across sessions (Fig. 1)
  - However, correlation between session data was low
- For the WPLI and IC methods, measurement error decreased as the frequency range increased
- In general, LE decreased as the level of task demand increased in difficulty (consistent with prior work)
- The LE method had the best classification performance in both the ternary and binary situations
- The SVM trained with a polynomial kernel achieved the highest mean accuracy in ternary (89%) and binary (97%) classification
- The results of classification suggest that the LE method based on MVGs can possibly serve as a biomarker of mental workload
- This work is still limited in that we only investigated connectivity between two regions at a time (cortical networking can occur between more than two)
- There were significant challenges with regard to the computational intensity of metric processing

Future Work

- Use simulated EEG to further investigate the properties of MVGs formed from EEG time series
- Compare the results of sensor-space and source-space connectivity analysis using MVGs
- Investigate the potential of FC-based methods to serve in a framework for mental workload assessment during long-term spaceflight missions
- Use MVG-based features as inputs for real-time decoding of mental workload in a passive brain-computer interface

References

1. Hinss, M., Jahanpour, E., Somon, B., Pluchon, L., Dehais, F., & Roy, R. (2023). *Scientific Data*, 10(1), 85.
2. Teymourlouei, A., Stone, J., Gentili, R., & Reggia, J. (2023). 16th Ann. Conf. on Brain Informatics, *Springer*.
3. Lacasa, L., Luque, B., Ballesteros, F., Luque, J., & Nuno, J. (2008). *Proceedings of the National Academy of Sciences*.
4. Škrlj, B., & Renoust, B. (2020). *Applied Network Science*, 5(1), 1-34.
5. Bland, J., & Altman, D. (1996). *BMJ: British Medical Journal*, 312(7047), 1654.

Acknowledgments

This work was supported in part by the Maryland Space Grant Consortium.