Multiplex Networks for Rapid Mental Workload Classification

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Introduction

- Passive brain-computer interfaces (pBCI) require an accurate method for classification of mental workload (MWL) using a small segment of brain activity.
- Classification of MWL has been demonstrated in previous work [1], but strong performance has not been shown at small sample sizes (< 10 seconds).
- In this work, we introduce a novel method to classify EEG signals (5-second windows) using the structural properties of multiplex temporal networks (MTNs).
- A multiplex network is a structure composed of two or more graphs, known as layers. We examine the edge overlap of these structures – that is, the tendency of layers to share the same edges.

Methods

- The simultaneous task EEG workload dataset (STEW) was used. Participants (n=48) engaged in multitasking to induce higher workload.
- Classification was performed individually on each participant's data.
- 10 EEG Channels were used for feature extraction. The signals were filtered of artifacts and segmented into 5-second windows.
- Delta, theta, alpha, beta, and gamma frequencies were considered.
- The natural visibility graph (VG) algorithm was used to map a time series to a complex network [2].
- The VG of each channel is assembled into layers of a single MTN, and a unique MTN exists for each 5-second period.
- To examine the structural property of the MTNs, edge overlap (also called *entanglement*) was measured [3].
- These properties are fed as inputs to a vector machine (SVM) classifier to predict the level of MWL.

References

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2. Lacasa, L., Luque, B., Ballesteros, F., Luque, J., & Nuno, J. (2008). From time series to complex networks: The visibility graph. *Proceedings of the National Academy of Sciences*.
3. Battiston, F., Nicosia, V., & Latora, V. (2014). Structural measures for multiplex networks. *Physical Review E*, 89(3), 032804

Computational Model

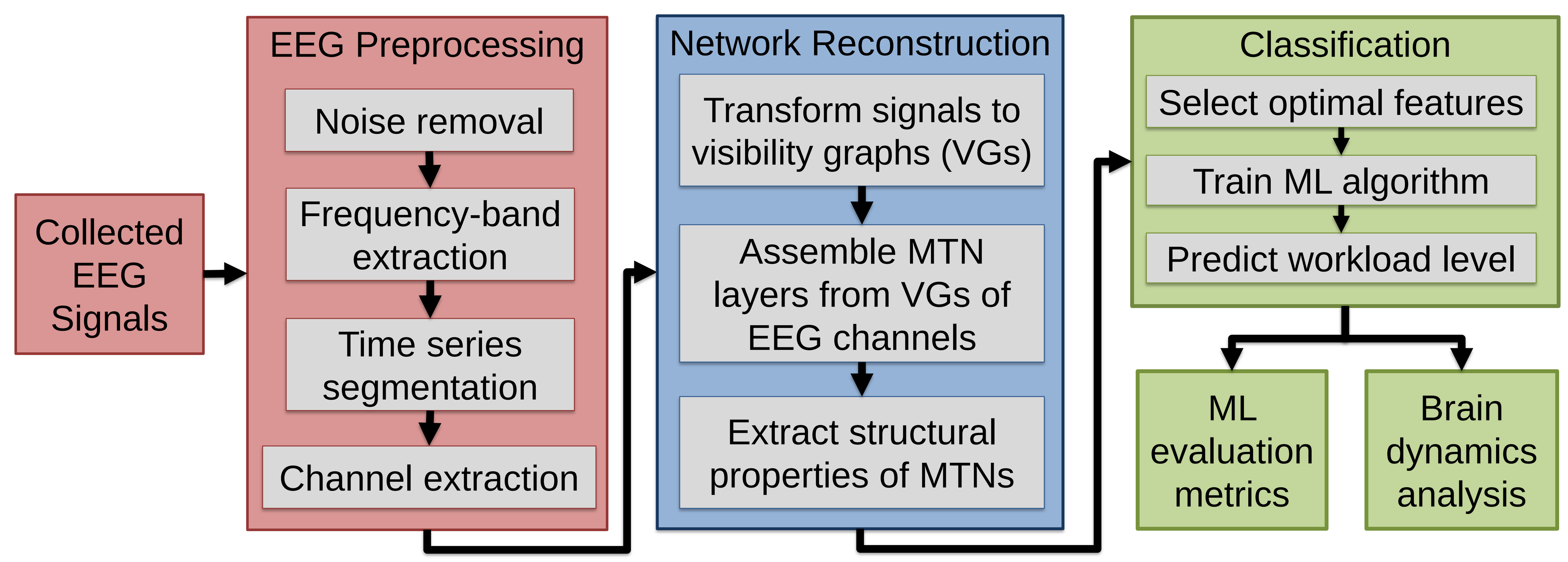

Fig 1. Computational model for classification of MWL. The collected EEG data is processed by means of filtering and segmentation. Processed signals are transformed into graphs by means of the VG algorithm. The VGs for all channels are then assembled into an MTN, whose properties are extracted. Specifically, the metrics with respect to edge overlap are computed. These are fed to ML classifiers which then predict the level of workload taken by the EEG.

Results

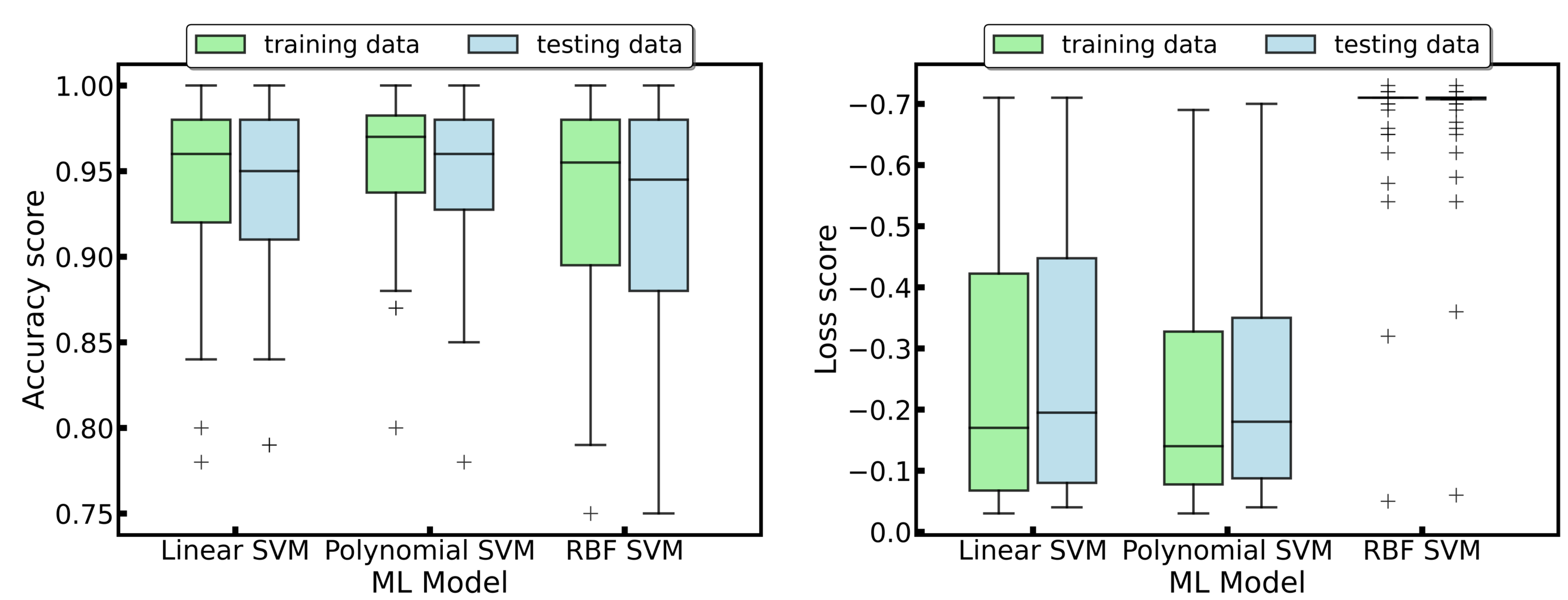

Fig. 2. Left panel: accuracy scores of three different SVM-based classifiers (variations of the kernel; linear function, polynomial function, radial-based function). Right panel: associated loss scores. Performance metrics are computed for each participant's data.

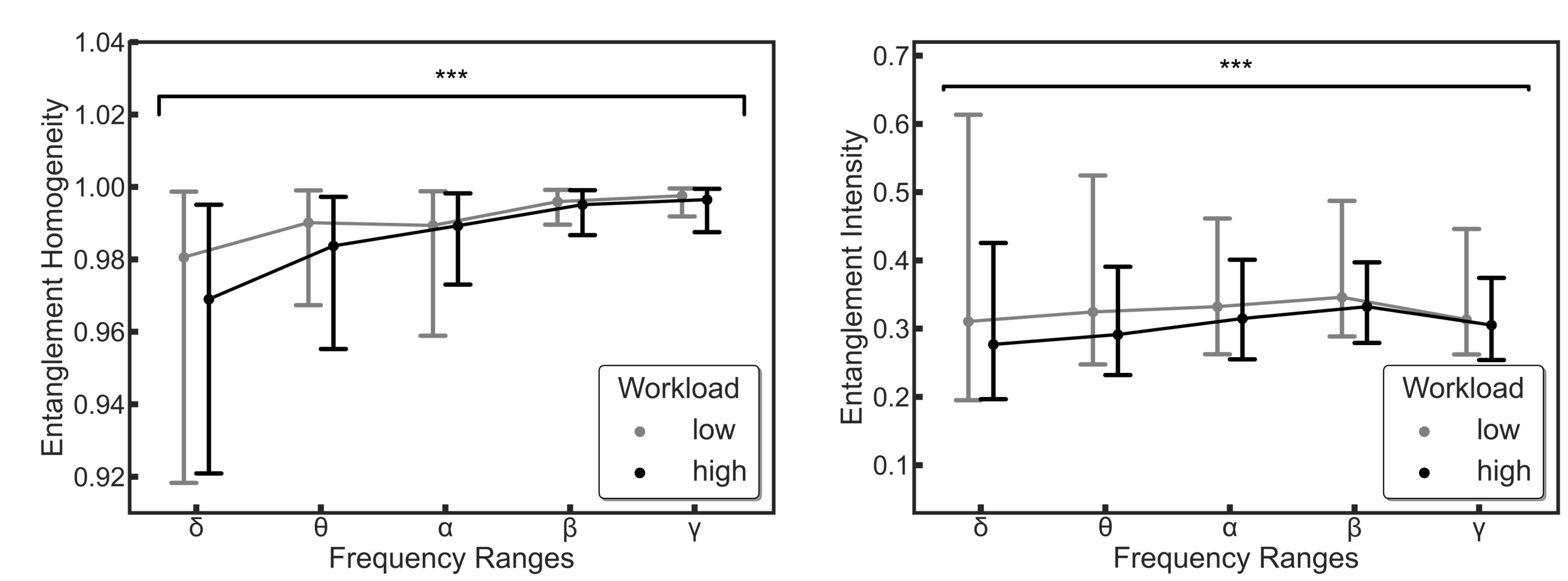

Fig. 3. Analysis of brain dynamics. Left panel: average similarities of edge overlap (denoted *homogeneity*) in individual frequency ranges. Right panel: average amount of overlap in the MTN (denoted *intensity*). Statistical significance is denoted as: ***p<0.001.

Broader Impact

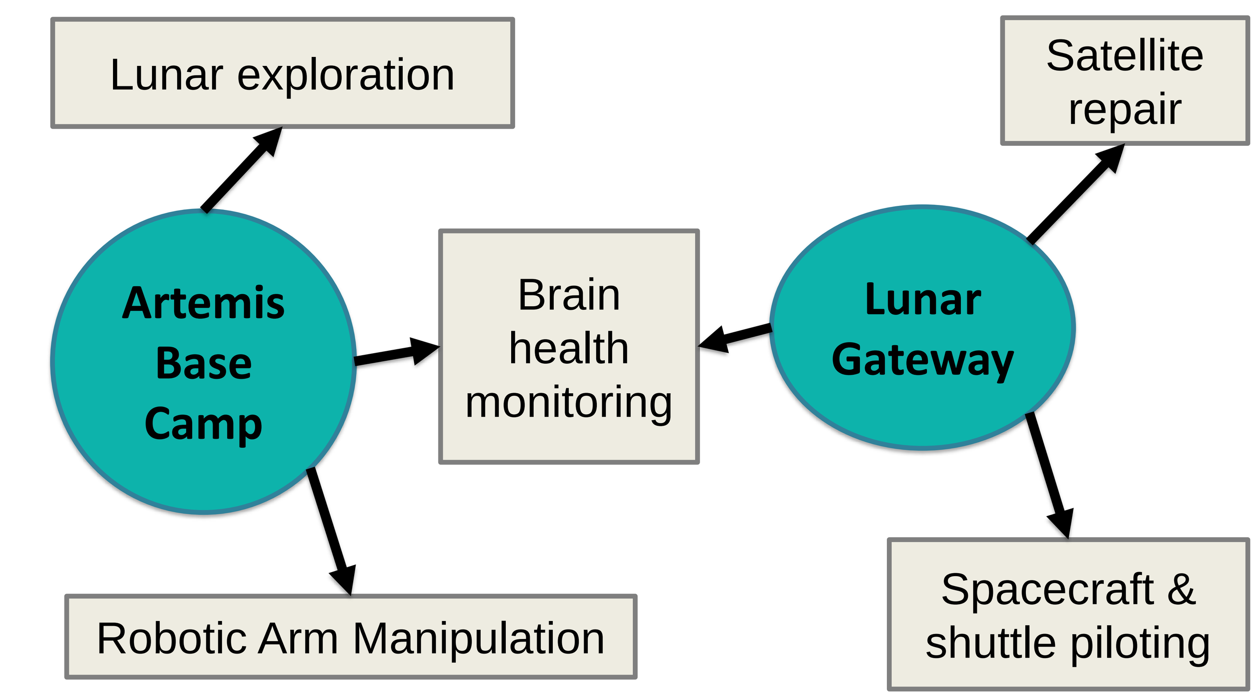

Fig 4. Examples of a pBCI application for space exploration.

- One application of pBCI is NASA space exploration missions (e.g., Artemis).
- Use of AI or robotic assistance *when required*, with the objective of not depleting limited resources and maintaining performance.

Discussion

- In this work we have i) built upon an existing methodology for mental workload classification [1] and ii) introduced a new technique for feature extraction for MWL classification.
- The main result of this work is the ability to classify **shorter EEG segments** with a high accuracy (≥95%).
- The best-performing classifier was the SVM with a polynomial kernel (95% average accuracy; average loss < -0.2).
- The performance of the SVM with linear kernel was slightly inferior to that of the polynomial SVM.
- The analysis showed the edge overlap metrics were discriminatory (statistically significant) between low and high MWL.
- Future work will focus on real-time pBCI:
  - Modifications to the approach presented here.
  - Polynomial vs. linear SVM
  - Continuous fluctuations of MWL (not low/high binary states).
  - Cognitive-motor tasks involving human-robot teaming.

Acknowledgments

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