DOI: 10.3217/978-3-99161-050-2-049

Addressing the Non-stationary Learning Problem with Graph Attention Networks in Motor Imagery

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Introduction: ALS progression causes non-stationary EEG signals, challenging methods like Common Spatial Patterns (CSP). While adaptive BCI research addresses non-stationarity and cross-session adaptation, they often rely on few sessions from healthy subjects [1] thereby neglecting to truly tackle the issue. Representing EEG signals as graphs provides a dynamic framework for decoding neuronal interactions with reduced computational cost, improving motor imagery classification in the face of non-stationarity. We propose using Graph Attention Networks to enhance classification accuracy over sessions, advancing longitudinal, robust BCIs for real-world applications [2].

Material, Methods and Results: We use two multi-session datasets: 25 healthy subjects (SHU dataset: 5 sessions, 500 trials/class) and 8 ALS patients (4 sessions over 2 months, approx. 160 trials/class), both performing Left and Right Motor Imagery. A novel 3 Layer GAT model (GAT Layer, ReLu, GraphNorm per layer) ($\approx$7000 Parameters) with Phase Locking Value input is trained on the first session of each dataset, with subsequent sessions used for testing. The performance is compared against Band Power of each electrode with LDA, CSP with SVM, EEGNet ($\approx$ 3000 Parameters), and DeepConvNet ($\approx$ 180000 Parameters).

Conclusion: BCI subjects from diverse cohorts and varying performance levels consistently achieve better outcomes with PLVGAT compared to alternative state-of-the-art methods as demonstrated in Fig. 1, which are often computationally intensive. This underscores PLVGAT's effectiveness in capturing dynamic brain connectivity, providing a more accurate and adaptable solution for longitudinal motor imagery classification across larger cohorts. Notably, the model excels with participants who struggle with traditional techniques, thereby addressing BCI Inefficiency and improving usability.

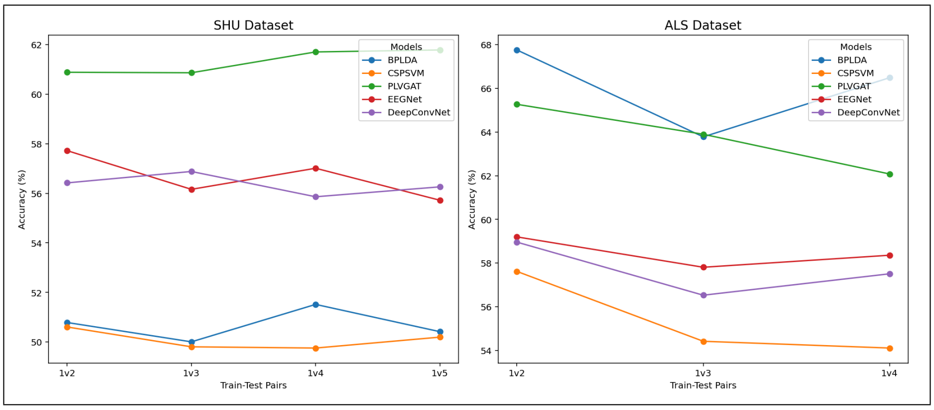

Figure 1: *Cross session accuracies over SHU and ALS datasets with five models including PLVGAT*

Acknowledgments and Disclosures: This work was supported by the EPSRC Doctoral Training Program (EP/W524335/1). The authors thank Dr. Geronimo from Penn State University for providing the data.

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