A Deep Learning Approach for Identifying Interpretable Neural Markers for Adaptive Deep Brain Stimulation in Parkinson's Disease

aDBS holds immense promise for advancing the treatment of Parkinson's disease (PD) by overcoming the limitations of conventional, open-loop stimulation, which often leads to side effects and sub-optimal symptom control. A core challenge impeding the development of aDBS is the identification of robust, real-time neural markers of motor impairment. Traditional linear models, such as those based on SPoC coupled with LDA, are often insufficient as they may fail to capture the complex, nonlinear dynamics inherent to PD pathophysiology.

This project addresses this challenge by proposing a DL approach to identify dynamic, patient-specific neural markers from LFP and potentially ECoG recordings. Here, the DPAD model by Sani et al. (2024) will be used to predict an objective metric from the CopyDraw experiments such as tracing velocity or the z-motor score (Dold et al., 2025). The model utilizes a two-section Recurrent Neural Network (RNN) architecture that uniquely separates the system's latent state, $\mathbf{X} \in \mathbb{R}^{k \times d}$ where k is the timestamp and d is a number of latent dimensions, into two components; there are four steps to predict the z-motor score. The first section of the RNN is trained to identify a latent subspace, $\mathbf{X}^{(1)}$, that is maximally predictive of behavior, the z-score, while the second section then learns a separate subspace, $\mathbf{X}^{(2)}$, that captures the residual neural dynamics not explained by the first. The model also explicitly learns to map these latent states back to the observed neural and behavioral data. These can be implemented as two FFNNs, namely C_y and C_z, whose prediction influences the RNNs learning ability. In a future closed-loop application, the state of the prioritized latent space, $\mathbf{X}^{(1)}$, could be used to gate the DBS system, delivering stimulation only when the neural signature of a motor symptom is detected.

Additionally, the project will involve ablation studies to determine the importance of specific model components and neural features. I will use latent state analysis to interpret the learned dynamics and employ hypothesis testing to localize the sources of nonlinearity, thereby statistically determining which component's nonlinearity is most critical for predicting behavior. The performance of this RNN-based approach will be benchmarked against established linear techniques, specifically SPoC for the regression task of predicting the continuous motor score. All analyses and model development will be conducted on a subject-by-subject basis to account for high inter-individual variability.

References

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