## Abstract:

Electroencephalography (EEG) remains a primary window into human brain activity owing to its high temporal resolution, low cost, and non-invasive nature. Yet its practical use in brain–computer interfacing and neurorehabilitation is constrained by subject variability, cumbersome electrode setup, and reliance on heavily parameterized learning models that offer little interpretability. This thesis develops analytical, graph-theoretic and information-theoretic tools that address these constraints without depending on deep learning architectures.

First, a spatiotemporal graph framework is proposed in which EEG electrodes form graph nodes and brain-state transitions are detected by tracking principal angles between invariant eigenspaces across successive time windows. Incorporating temporal structure yields more robust and accurate transition detection than spatial-only graph models. Second, the influence of electrode configuration is examined systematically: reducing electrode density degrades transition-detection accuracy, whereas the specific scalp region from which electrodes are drawn has limited influence, a finding supported by pairwise statistical testing across subjects. Third, sparse graph representations and the temporal dynamics of subspace characteristic representation vectors are analysed to study the decodability of motor imagery, offering an analytical account of why compact electrode subsets can remain informative. Finally, two channel-selection frameworks are introduced. The first combines normalized mutual information between channels with inter-electrode distance to favour spatially distributed, non-redundant electrodes. The second ranks channels by Kullback–Leibler divergence from the central reference electrode Cz, using distributional proximity to an established motor electrode as a relevance proxy. Both selection stages operate without subject-specific calibration and, on benchmark motor imagery datasets, achieve decoding accuracy comparable to state-of-the-art channel-selection methods while remaining computationally efficient and interpretable.

Together, these contributions form an analytical pipeline from brain-state transition detection to motor imagery decoding, supporting scalable and interpretable EEG-based neurotechnology.