



## Ph.D. Dissertation Defense

<b>Candidate:</b>	Meng Jiao
<b>Degree:</b>	Doctor of Philosophy
<b>School/Department.:</b>	Charles V. Schaefer, Jr. School of Engineering and Science Department of Systems and Enterprises
<b>Date:</b>	Friday, November 22, 2024
<b>Time:</b>	2:00 pm – 4:00 pm
<b>Location:</b>	Babbio 503
<b>Title:</b>	Learning from Sparse and Graph Structured Electrophysiological Data for Brain Disorder Diagnosis
<b>Chairperson:</b>	Dr. Feng Liu, Department of Systems and Enterprises, Charles V. Schaefer, Jr. School of Engineering and Science
<b>Committee Members:</b>	Dr. Ting Liao, Department of Systems and Enterprises, Charles V. Schaefer, Jr. School of Engineering and Science Dr. Zhongyuan (Annie) Yu, Department of Systems and Enterprises, Charles V. Schaefer, Jr. School of Engineering and Science Dr. Jacqueline Libby, Department of Mechanical Engineering, Charles V. Schaefer, Jr. School of Engineering and Science Dr. George McConnell, Department of Biomedical Engineering, Charles V. Schaefer, Jr. School of Engineering and Science Dr. Raviraj Nataraj, Department of Biomedical Engineering, Charles V. Schaefer, Jr. School of Engineering and Science

### Abstract

Understanding complex neuronal firing patterns and interactions between neural circuits at different brain regions is essential for uncovering the mechanisms of brain function and dysfunctions. Electrophysiological Source Imaging (ESI) refers to reconstructing underlying cortical and subcortical electrical activities from electroencephalography (EEG) or magnetoencephalography (MEG) recordings. ESI is crucial for both neuroscience research and clinical applications, serving as an essential tool for capturing brain source signals with high temporal resolution. However, solving the ESI inverse problem remains challenging due to its ill-posed nature. To obtain a unique solution, traditional algorithms emphasize incorporating predesigned neurophysiological priors to restrict the solution space, while deep learning frameworks aim to directly learn the mapping from scalp EEG/MEG measurements to underlying brain sources in a data-driven manner, eliminating the need for handcrafted priors. Building on this, this dissertation proposes several ESI algorithms designed to capture the complexities of brain activity by leveraging sparse and graph-structured EEG/MEG signals, especially in cases involving extended source activities.

A key application of ESI is localizing epileptogenic zones (EZs) in patients with focal epilepsy. Beyond electromagnetic signals, seizure semiology, which describes the signs and symptoms a patient exhibits during seizures, also provides valuable insights for identifying EZs. Recently, large language models (LLMs), particularly chatbots, have been increasingly adopted in medical informatics. Therefore, this dissertation further investigates employing LLMs to infer EZ locations with seizure semiology as input queries. This work demonstrates the potential of integrating generative artificial intelligence (AI) with clinical text data for epilepsy diagnosis, offering a novel alternative distinct from neuroimaging techniques.

Apart from EZ localization, this dissertation also tackles sleep apnea (SA), a widespread condition with serious health implications, including cardiovascular disease, diabetes, and impaired cognitive function. With the



increasing prevalence of SA, timely and accurate SA detection has become essential for effective intervention and health management. In this work, we propose a novel deep learning framework to detect SA events by leveraging electrocardiogram (ECG) signals. This work further demonstrates the potential of electrophysiological signal analysis for identifying neurological and physiological conditions.