Title: Combining Sparse Signal Processing with Deep Learning for EEG/ECG Analysis: A Model-Based Deep Learning Approach

Introduction

Electroencephalogram (EEG) and electrocardiogram (ECG) signals are vital in diagnosing and understanding neural and cardiac activity. These signals, however, are often noisy and high-dimensional, necessitating advanced processing techniques. Sparse signal processing methods, like those developed by Professor Ivan and others, provide a powerful framework for analyzing these signals by decomposing them into meaningful components. Meanwhile, deep learning has advanced the field by automating feature extraction and classification, although it often lacks interpretability and requires large datasets. My research seeks to combine the strengths of sparse signal processing and deep learning to develop an interpretable, efficient framework for analyzing EEG and ECG signals, improving both accuracy and robustness without relying on massive datasets.

Problem Statement

There is a clear need to combine sparse signal models with deep learning to improve the analysis of EEG/ECG signals. The core question of this thesis is how to integrate sparse signal priors into deep neural networks, enhancing interpretability, efficiency, and robustness. This proposal aims to develop a model-based deep learning framework, combining established sparse signal processing techniques with modern deep learning approaches, to create a novel methodology that bridges the gap between theory-driven and data-driven signal processing.

Background and Motivation

Sparse signal processing exploits the inherent sparsity in EEG and ECG signals, separating transient events from background noise using optimization methods. Techniques like Selesnick's BEADS and DETOKS algorithms offer interpretable models for signal decomposition but require manual tuning. On the other hand, deep learning models, while powerful, often lack interpretability and require large datasets, which are not always available in biomedical applications. Recent advancements, such as algorithm unrolling and the integration of sparse priors in deep networks, offer a promising direction for combining the best of both worlds.

Proposed Framework and Methodology

This research will develop a model-based deep learning framework that integrates sparse signal processing principles into neural network architectures. The primary steps are:

1. **Unrolling Sparse Signal Algorithms into Neural Networks**: We will adapt algorithms like BEADS, which remove baseline wander and denoise signals, by

unrolling their iterative steps into neural network layers. Each layer of the network will correspond to a signal processing operation (e.g., filtering, thresholding), with tunable parameters learned during training.

2. **Incorporating Sparse Priors via Learned Penalties and Proximal Operators**: Sparse priors will be directly integrated into the network's architecture by incorporating regularization terms like the $\ell 1$ norm to enforce sparsity. This will encourage the network to learn a sparse representation of the signals, similar to traditional sparse coding methods, but with the flexibility of a deep learning framework.

3. **Theoretical Analysis and Model Evaluation**: Alongside developing the models, we will rigorously analyze their expressive power, convergence, and stability. We will compare the performance of the unrolled sparse models with traditional deep learning models on tasks such as denoising and event detection in EEG/ECG signals.

Relation to Prof. Ivan Selesnick's Work

This thesis directly builds on Prof. Ivan's work in sparse signal processing, particularly his development of algorithms like BEADS and DETOKS. By unrolling these algorithms into trainable models, we aim to extend their capabilities and introduce new theoretical insights into how sparse signal processing techniques can be integrated with deep learning. The work will reference and use Prof. Selesnick's algorithms as the basis for the deep learning models, ensuring that the models remain grounded in established signal processing principles.

Expected Contributions

1. **Hybrid Signal Processing-Deep Learning Framework**: A novel deep learning framework that integrates sparse signal processing models, providing a more interpretable and efficient approach to biomedical signal analysis.

2. **Theoretical Insights into Unrolled Networks**: We expect to gain new theoretical insights into how unrolled networks behave and how the integration of sparse priors affects model training and performance, including how much less data is required compared to traditional deep learning models.

3. **Practical Applications**: The framework will be validated on real-world tasks such as ECG denoising and EEG event detection, where we expect it to outperform black-box deep learning models in terms of interpretability and efficiency.

4. **Contribution to Prof. Selesnick's Lineage of Work**: This research will extend Prof. Selesnick's sparse signal processing techniques into the realm of deep learning, creating a new class of learnable algorithms that combine theoretical rigor with data-driven flexibility.

Conclusion

This thesis proposes a novel approach to EEG/ECG analysis by combining sparse signal processing with deep learning, offering improvements in interpretability, efficiency, and robustness. By developing models that integrate prior knowledge with data-driven learning, the research aims to make significant contributions to both the fields of biomedical signal processing and deep learning, with the potential for broader applications in medical diagnostics and signal analysis.

References:

Key Sources from Prof. Ivan Selesnick's Work

1. **Selesnick, I. W.** (2011). *Resonance-based signal decomposition: A new sparsity-enabled signal analysis method.* Signal Processing, 91(12), 2793–2809.
2. **Ning, X., Selesnick, I. W., & Duval, L.** (2014). *Chromatogram baseline estimation and denoising using sparsity (BEADS).* Chemometrics and Intelligent Laboratory Systems, 139, 156–167.
3. **Parekh, R., & Selesnick, I. W.** (2015). *Convex fused lasso denoising with non-convex regularization and its use for pulse detection.* IEEE Transactions on Signal Processing, 63(2), 480–490.

Deep Learning & Unrolling References

4. **Gregor, K., & LeCun, Y.** (2010). *Learning fast approximations of sparse coding.* In ICML.
5. **Monga, V., Li, Y., & Eldar, Y. C.** (2021). *Algorithm unrolling: Interpretable, efficient deep learning for signal and image processing.* IEEE Signal Processing Magazine, 38(2), 18–44.
6. **Tolooshams, B., et al.** (2024). *Neural architecture design for interpretable electrophysiology.* IEEE Transactions on Biomedical Engineering (early access).

Applications in EEG/ECG + Hybrid Models

7. **Jiao, Z., Zhang, Y., Li, W., et al.** (2024). *XDL-ESI: An explainable deep learning framework for EEG source imaging.*

8. **Lv, J., Li, Y., Sun, Y., et al.** (2022). *Proximal gradient-based deep network for image restoration.* IEEE Transactions on Neural Networks and Learning Systems.
9. **Zhang, J., et al.** (2022). *Emotion recognition using EEG signals based on a sparse autoencoder and CNN-LSTM network.* Biomedical Signal Processing and Control, 71, 103163.
10. **Rajpurkar, P., et al.** (2017). *Cardiologist-level arrhythmia detection with convolutional neural networks.*