Contrastive learning on Transformer Encoders for sEEG-based SOZ Detection

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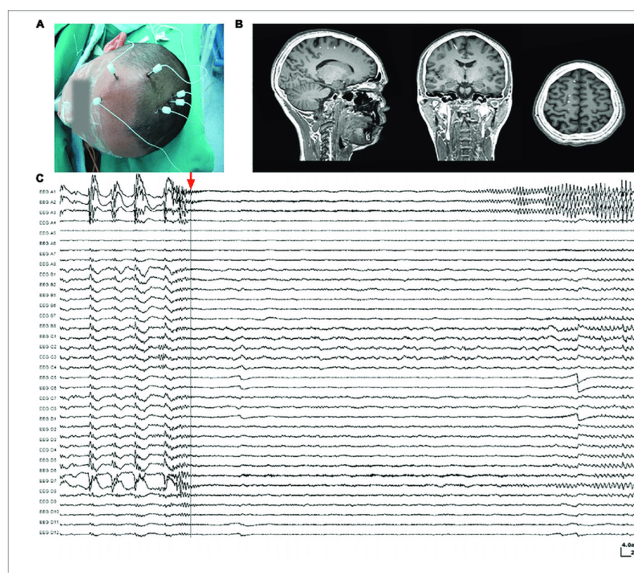
Introduction

For drug-resistant focal epilepsy, neurosurgical intervention to resect the epileptogenic zone (EZ) can be the only curative treatment. One aspect of the preparatory localization of the Seizure Onset Zone (SOZ) is to analyze stereo-EEG (sEEG) signals, which are intracranial measures at electrodes (typically between 8 and 12, each with 10 to 12 contact points). We develop a novel Seizure Onset Zone detection model based on a Transformer[1] encoder, as well as a new spatial contrastive pre-training framework based on channel-specific learned representations. The model processes heterogeneous sEEG records from different patients, using both ictal and interictal data. The supervised contrastive strategy minimizes representational similarity between SOZ vs non-SOZ channels.

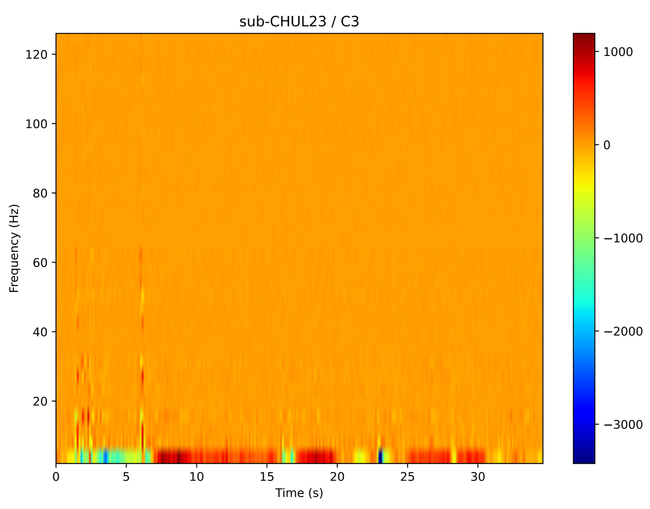


sEEG electrodes and recordings. Figure from [2]

We employ a public sEEG dataset from the Hospital of the University of Pennsylvania (HUP)[3] alongside a private dataset from Lyon University Hospital (CHUL), which we processed to ensure compliance with the Brain Imaging Data Structure (BIDS) standard[4].

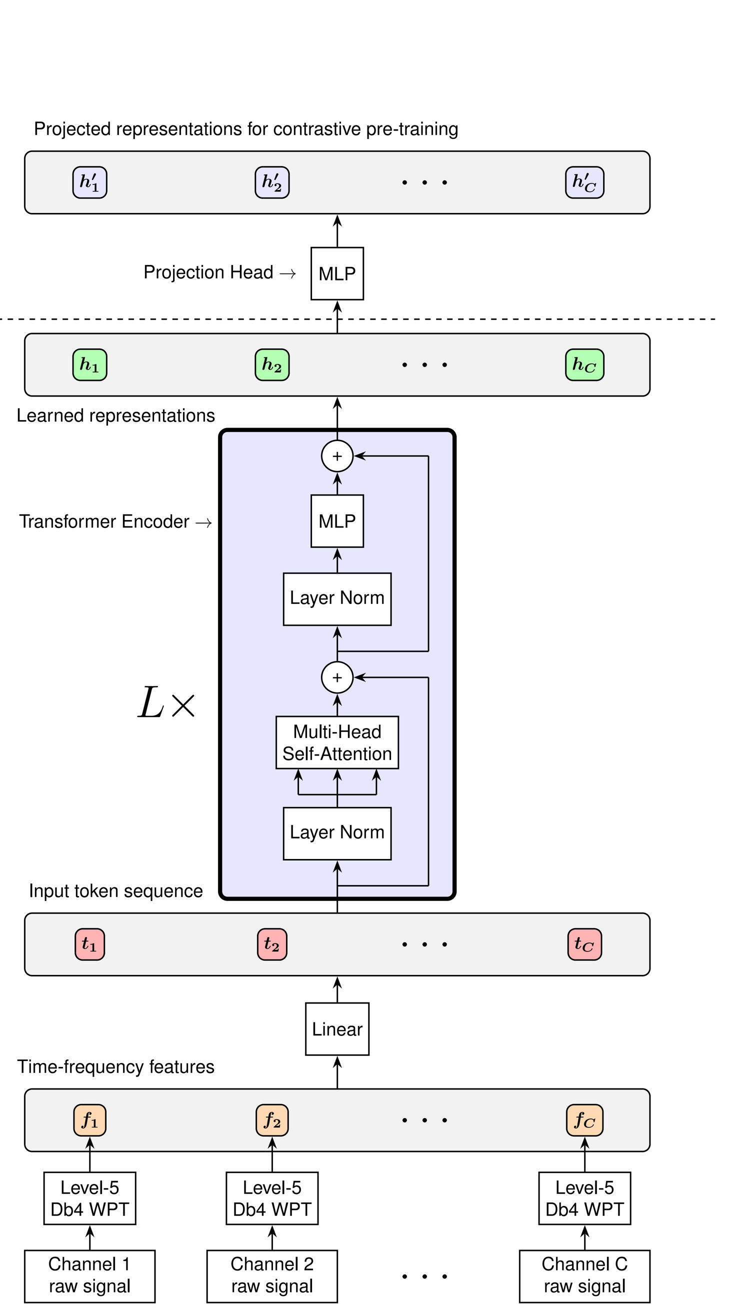
Time-frequency features

We use a 5-level Daubechies-4 (Db4) Wavelet Packet Transform (WPT)[5] to analyze sEEG signals. This transform provides good time-frequency localization, creating features sensitive to both transient events like spikes and specific narrowband oscillations like ripples[6, 7]. The resulting sub-band decomposition helps distinguish these pathological patterns from background activity for subsequent modeling.

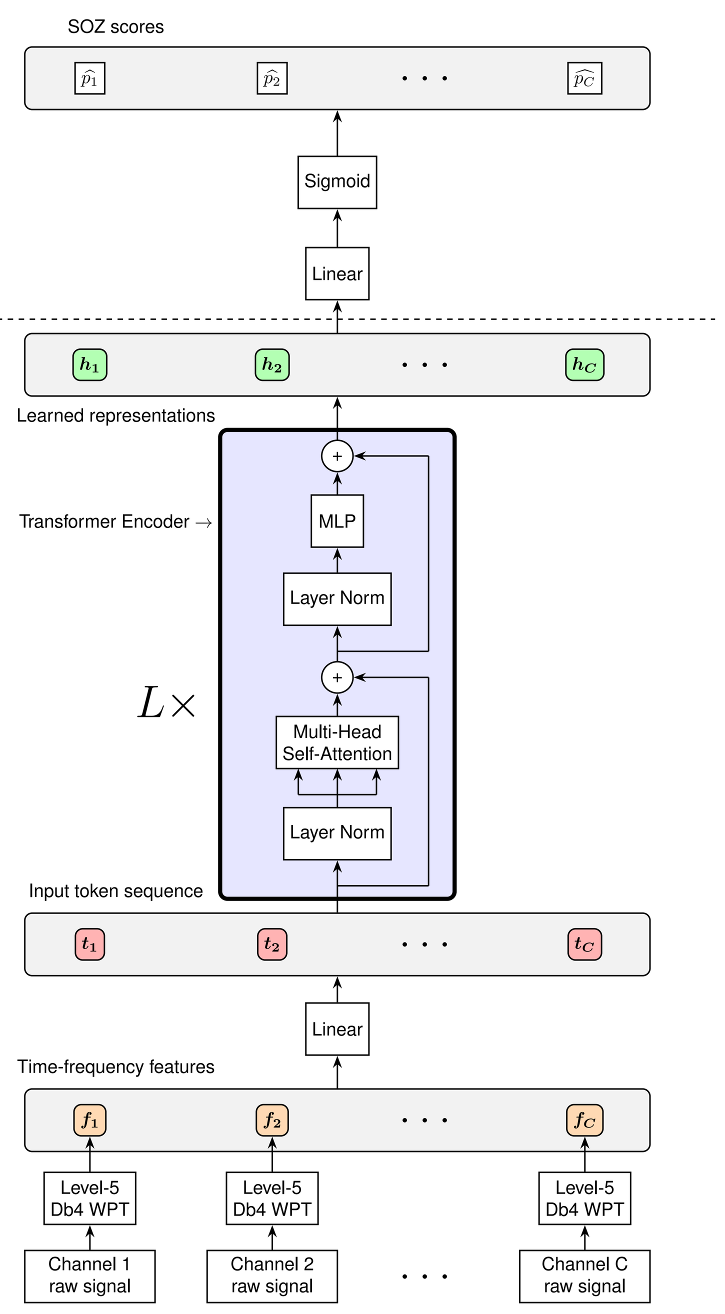


Wavelet Packet Transform of a 35 second clip for a given channel.

Model



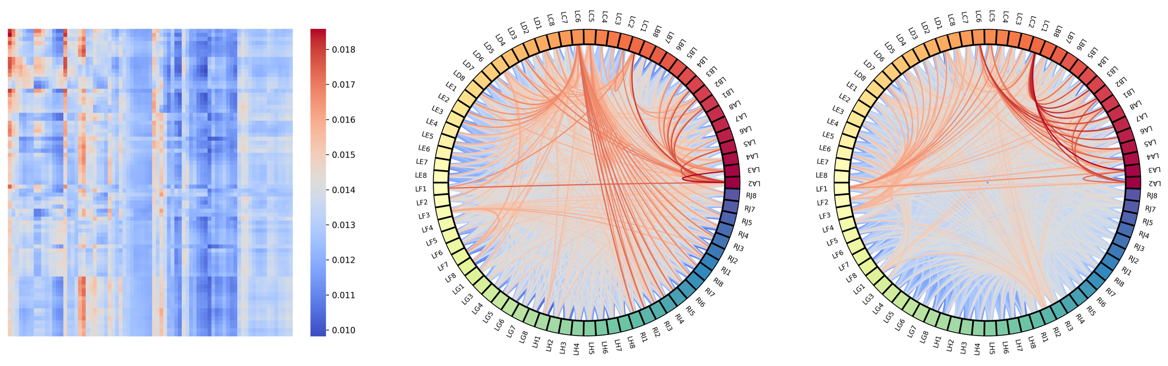
Encoder with contrastive pre-training head.



Encoder with fine-tuning head.

Attention maps as directed connectivity graphs

We interpret the Transformer's attention maps $A = \text{softmax}\left(\frac{QK^\top}{\sqrt{d_K}}\right)$ as directed graphs, analogous to functional connectivity networks used in neuroscience[8, 9, 10, 11]. Analyzing these graphs across layers and heads reveals learned dependencies between input channels and links attention mechanisms with traditional brain signal analysis.



Attention map seen as a directed graph. The center graph shows the upper right triangle of the attention matrix, while the rightmost graph shows the lower triangle. Attention flows from queries (line indices) to keys (column indices). Arrows not shown for clarity.

Contrastive Pre-training

We pre-train an encoder using Focal Class-Balanced Supervised Contrastive Loss[12, 13, 14] to learn channel embeddings ($\boldsymbol{z}_i$) that group channels by SOZ label and handle class imbalance within patient segments.

The loss aggregates over anchor channels i:

$$\boxed{\mathcal{L}_{\text{F-CB-SC}} \propto \sum_{i:|P(i)|>0} w_i^{\text{CB}} \cdot \underbrace{\frac{-1}{|P(i)|} \sum_{p \in P(i)} \overbrace{(1-p_{ip})^{\gamma}}^{\text{Focal Modulation}} \log(p_{ip})}_{\text{Avg. Focal SupCon for anchor } i}}$$

with:

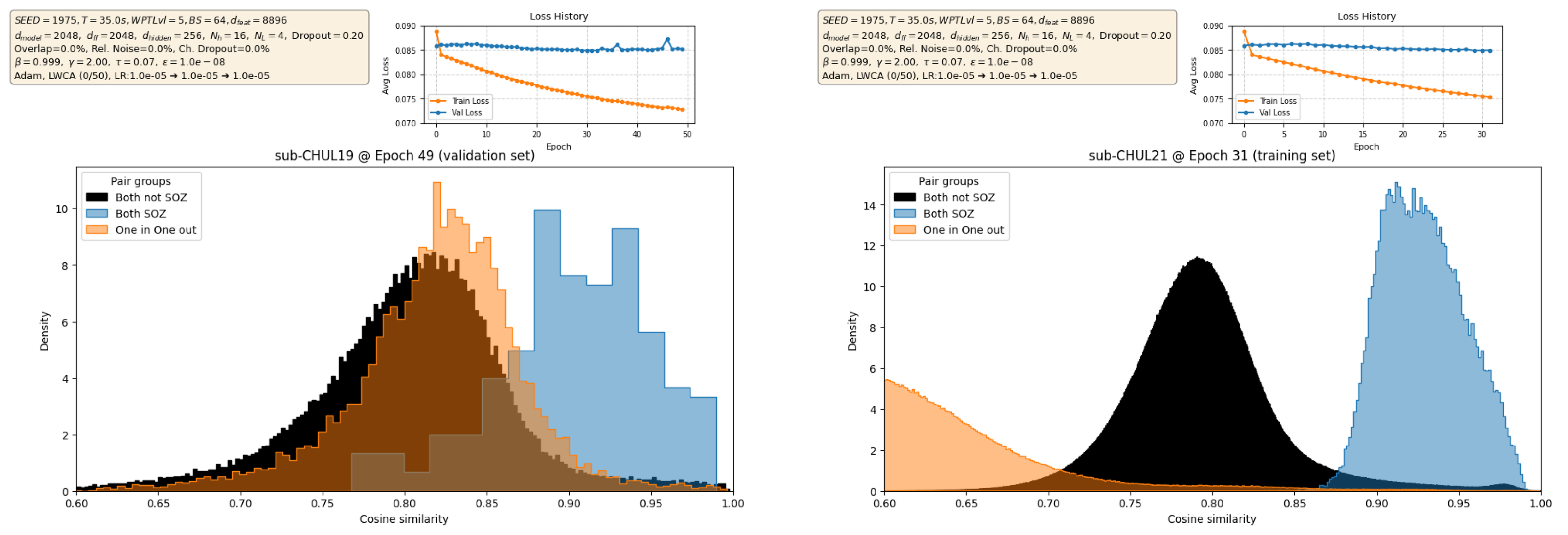
- Class Balance Weight (using effective N):

$$w_i^{\text{CB}} = \frac{1-\beta}{1-\beta^{N_{y_i}}+\epsilon}$$

- Contrastive Probability (for positive pair p):

$$p_{ip} = \frac{\exp(\text{sim}(\boldsymbol{z}_i, \boldsymbol{z}_p)/\tau)}{\sum_{k \in A(i)} \exp(\text{sim}(\boldsymbol{z}_i, \boldsymbol{z}_k)/\tau)}$$

Hyperparameters: τ (temperature), β (class balance, e.g. 0.99), γ (focal focus). This loss pushes same-class embeddings together and different-class embeddings apart, weighting rare classes (β) and hard positive pairs (γ) more heavily.



Fine-tuning for SOZ Detection

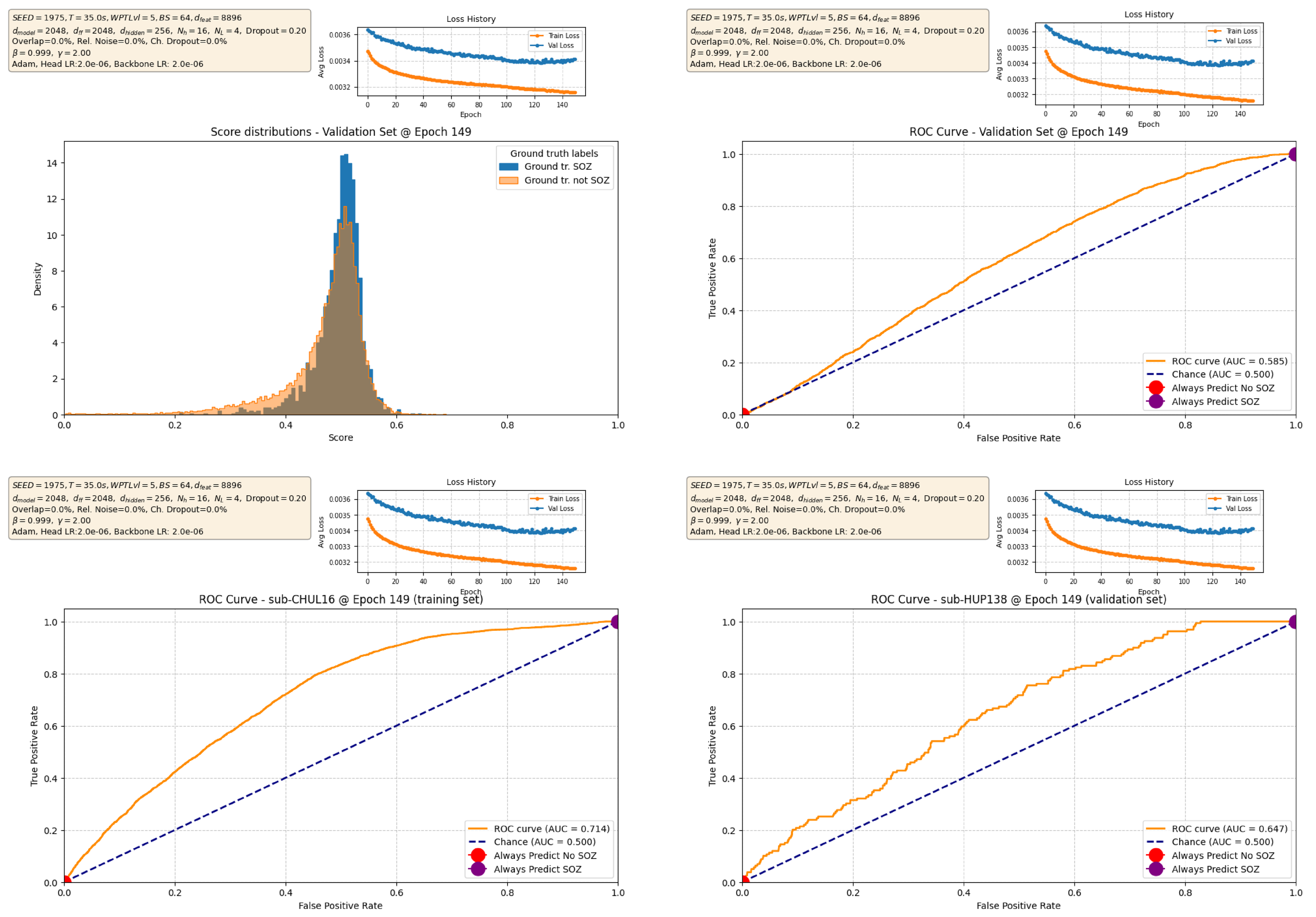
Fine-tuning adapts the model to predict SOZ probability ($y_n = 1$) per channel. We continue to mitigate data imbalance, employing similar strategies as in pre-training through the use of Focal Class-Balanced BCE Loss.

The loss aggregates over individual channels n:

$$\boxed{\mathcal{L}_{\text{F-CB-BCE}} \propto \sum_n \underbrace{w_n^{\text{CB}}}_{\substack{\text{Balances channel class} \\ \text{(via } \beta,\, N_{y_n})}} \cdot \underbrace{(1-p_t^n)^{\gamma}}_{\substack{\text{Focuses on hard} \\ \text{predictions (via } \gamma)}} \cdot \underbrace{\text{BCE}(x_n, y_n)}_{\substack{\text{Standard Binary} \\ \text{Cross Entropy}}}}$$

where:

- x_n is the logit output for channel n; y_n is the true label.
- p_t^n is the predicted probability ($\sigma(x_n)$ or $1-\sigma(x_n)$) for the true class y_n.



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